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Using latent class models to explore cross-national typologies of public engagement with science and technology in Europe

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Abstract

Public engagement with science and technology is a central theme in the field of Public Understanding of Science (PUS), particularly in Europe. Alongside public consultation exercises and similar activities aimed at generating engagement, there is a need for good survey indicators of the general climate for engagement with science and technology among the public. With internationally focused PUS studies increasing in prominence, such survey indicators should ideally characterise engagement in approximately the same way across a range of countries, to facilitate sensible cross-national analyses involving this construct.

This paper presents cross-national analyses of two sets of questions posed in the Eurobarometer survey on public perceptions of biotechnology, conducted in 2002 in fifteen European countries. The items analysed capture a range of elements of the concept of engagement, both with science and technology in general and with biotechnology in particular. Latent class models are used to explore typologies of types of engagement: substantively, to understand their content, and methodologically, to identify items which do not work well in these classifications. The analyses are also used to assess the statistical cross-national comparability of such typologies, and consequently to describe variations in levels of engagement across countries.

Introduction

The concept of public engagement is of central importance in the field of Public Understanding of Science (PUS) currently, particularly in Europe, where it is not so much a construct to be measured as an ideal to be enacted. In the UK, for example, the government's 'Science and Society' report (House of Lords, 2000) called for a new direction in PUS activities, moving away from the traditional one-way dissemination of information from scientists to laypeople, and towards a multi-way dialogue between scientists, civil society, politicians and the public (Miller, 2001). This participative turn in PUS is rooted in the aim of democratising the governance of science and technology, and attracts financial and other support from governments, inter-governmental bodies such as the European Commission, and independent institutions. Recently, for example, the UK government began funding a centre specifically devoted to creating and supporting public engagement with science and technology (Department for Innovation, Universities and Skills, 2008); public engagement has been on the agenda for the European Union for some time (Banthien, Jaspers, & Renner, 2003); and the Wellcome Trust, a large and well known independent medical research charity in the UK, has developed its own programmes and funding initiatives for public engagement activities (Wellcome Trust, 2005). One of the consequences of this new agenda for social scientists working in PUS is an increasing demand for them to play the roles not only of observers of this social context, but also of 'angels' (Bauer, Allum, & Miller, 2007), actively mediating and bolstering dialogue among science 'actors' and the public.

Alongside public dialogue exercises, however, there is a need for survey indicators of engagement. These can be useful in two ways. Firstly, they can provide constructive information for engagement exercises themselves: researchers involved practically in public consultation projects such as the UK's 'GM Nation?' have explicitly stated the need for good survey data, as components of such projects (Pidgeon et al., 2005) and as quality indicators in evaluations of them (Rowe, Horlick-Jones, Walls, & Pidgeon, 2005). Secondly, measures of engagement in public opinion surveys may constitute valuable tools for gauging the general climate for participation among the public (Bauer et al., 2007), giving an indication of the level and quality of participation which could potentially be achieved in engagement activities.

Survey measures of engagement with science and technology have indeed already been employed from time to time in quantitative analyses in PUS research. There is no single leading approach to deriving such measures, but a number of composite indicators can be cited in the literature which might be identified as more or less closely related to the idea of engagement. Jon Miller, for example, writes about the 'attentive public' for science, or for biotechnology, drawing on a model from political science (Almond, 1950). He creates a three-category ordinal classification of levels of attentiveness. To be part of the attentive public for an issue is to be interested in it, to feel informed about it, and to seek or be exposed to information about it via various media sources. To be interested but to feel uninformed, and also practically speaking be uninformed, is to be part of the 'interested' public. Those with any other combination of characteristics are classified as belonging to the unengaged class of the 'residual' public. Miller uses this typology in relation to science in general (e.g. Miller & Pardo, 2000) and to biotechnology in particular (e.g. Miller & Kimmel, 2001). In the latter study, Miller and Kimmel also use an ordinal measure of 'awareness' of biotechnology, as a combination of two criteria: having heard of biotechnology before and having talked about it with others. The resulting variable takes five categories, from having neither heard nor spoken about biotechnology before, to having both heard about it and spoken about it frequently with others. In a more recent study, Pardo, Midden, and Miller (2002) define a typology of 'informedness' about biotechnology on the basis of a combination of binary criteria: awareness versus lack of awareness, and high versus low knowledge. A slightly different angle is adopted in a study by Evans and Durant (1995) who define 'interest in science' as a combination of a number of items asking respondents to rate their levels of interest and their consumption of science-related media.

In contrast to these prescriptively defined measures of engagement, Gaskell et al. (2006) use a latent class analysis of a Eurobarometer survey on biotechnology to reach an empirically-derived classification what they term ‘engagement’ with biotechnology. From the analysis they identify four types of respondents among the European public: the ‘attentive’ public have high levels of awareness and knowledge about biotechnology; the ‘active’ are aware of biotechnology and are likely to have taken part in public meetings on the subject; ‘spectators’ report lower levels of exposure to biotechnology; and the ‘unengaged’ give negative responses to all indicators of engagement.

There is a notable absence in PUS literature of methodological scrutiny of these or any other survey indicators of the concept of engagement, in terms of either the form or the content of such measures. By contrast, methodological comments have been made on measures of attitudes towards science and technology (e.g. Pardo & Calvo, 2002), and measures of knowledge about science have attracted some sharp critiques. For example, the standard items[1] used for assessing science knowledge have been criticised for failing to cover types of science knowledge which are relevant for the layperson, and as a result possibly underestimating levels of scientific understanding (Irwin & Wynne, 1996). Peters (2000) has pointed out the bias in these items towards the Anglo-Saxon school science curriculum, which presents problems for cross-cultural comparisons using them. Raza, Singh and Dutt (2002) take up this point explicitly in their model of the ‘cultural distance’ of scientific facts tested in such survey items, which they apply cross-culturally within India. Furthermore, Pardo and Calvo (2004) test the measurement properties of scales created from these questions, and find that the variance of the scale is systematically smaller in more industrially advanced countries, calling into question the validity of cross-national comparisons using such scales.

Making comparisons between groups is a fundamental part of survey analysis. This paper is focused specifically on cross-national comparisons, which are notoriously problematic in survey research. I will not review here the considerable literature which already exists on this subject (see e.g. Harkness, van de Vijver, & Mohler, 2003 for an overview). It goes without saying that questionnaire items administered in several different languages and cultural contexts may carry varying meanings for respondents at these varying vantage points. Sensitive cross-national comparisons therefore need to attend as carefully as possible to the question of whether they are comparisons of like with like. This must realistically be a question of to what extent rather than whether, since equally within languages and cultural settings, people bring their own frames of reference to bear on the surveys in which they participate. It is an empirical question at what point varying interpretations of questions become so diverse as to make comparisons meaningless and misleading.

There are many ways of addressing this empirical question, none of which represents a panacea for cross-national survey research. The traditional approach is to draw as much as possible on supporting qualitative data about the cultures and languages involved in the survey. Another approach, not widely used in survey research to date, is to exploit the potential of statistical models for identifying items which 'function' in different ways between groups. The latter is the focus for this paper: in it, I hope to demonstrate how latent class models can be employed for this purpose. As well as being useful in particular for assessing cross-national comparisons, latent class models can be useful in general for assessing the measurement properties of composite indicators. Pardo and Calvo (2002) complain that many high profile PUS publications use 'conceptually fuzzy scales and indicators that fall short of the standards generally applied in other areas of social scientific research' (ibid., p.162). Latent class models can provide diagnostic information about which items do and which do not work together well to form measures of the concepts we wish to capture in PUS. In this paper I use them to explore how summary measures of engagement can be created from sets of survey items; to scrutinise the fitness for purpose of the items; and to explore how statistically valid comparisons of engagement can be made between respondents in different countries. Details of the specific models used are given below, following a brief introduction to the data to be analysed.

Data: Eurobarometer 58.0 on biotechnology

The data are taken from the Eurobarometer survey on biotechnology, conducted in 2002 in the then fifteen European Union (EU) member states. Two sets of questions are analysed, each designed to capture different elements of engagement. Table 1 gives frequencies of responses across the complete European data set for the first set of four items. These capture cognitive and affective aspects of engagement with science and technology in a broad sense: how interested and how knowledgeable respondents feel about the topic. They are hereafter referred to as the 'science' items. The table shows a relatively even spread of answers, with a tendency towards the middle position each time: to be interested, informed, understand science stories and suffer confusion in the face of conflicting stories, 'some of the time'. In contrast with many of the questions posed in the Eurobarometer, these contain very few 'don't know' (DK) responses; at most, 4 per cent (for the last question in the set).

The second set of items, presented in Table 2, are different in two respects: they focus specifically on biotechnology, and ask about behavioural elements of engagement rather than about cognition or affect; hereafter they will be referred to as the 'biotechnology' items. The first two ask only about hypothetical behaviours: would respondents, in principle, be willing to participate in a public forum or use the media to find out about biotechnology? These provoke much more equivocation, especially on taking part in public hearings and discussions, where 15 per cent of respondents will not be drawn, and 53 per cent would tend to decline to participate. Such a lack of enthusiasm for discussing biotechnology in a formal setting echoes low levels of experience of discussing it in any setting: the last two items ask for reports of actual behaviours – whether people have ever talked about biotechnology, and whether they have been exposed to coverage of biotechnology in various media forms. Fifty per cent of respondents have never talked about biotechnology with anyone. Vocal engagement may be a tall order, then. However, two thirds of respondents say they would be happy to engage with biotechnology in a more passive way, by reading articles or watching television programmes on the topic. This is not already a widespread habit, however; 41 per cent have not, in the last three months at least, heard or read about biotechnology in the mass media. Where they have done so, it is most commonly on television or in newspapers.

Methods: latent class models

Composite measures of engagement could be derived from these data in a number of ways. Among the four science items, for example, it would be fairly uncontroversial to describe as highly engaged those who are interested in and feel informed about science and technology 'most of the time' and who become confused by conflicting stories 'hardly any of the time'. Those giving mirror image responses could be called 'unengaged', and those who give the response 'some of the time' to all items could be thought of as ambivalent. However, with four items and three response options per item, many other combinations of responses might be given. In fact there are eighty-one (3^4) different possible response profiles; and in the European data set, all are observed. An eighty-one-category classification of engagement is of little use in any practical analyses. Adopting even a twenty-category scheme using the twenty most common response patterns would mean leaving a quarter of the respondents in the sample unclassified. Similar response profiles could be counted together to reduce the number of groups, but an arbitrary rule would have to be devised for this purpose. A better approach is to treat the relationship between types of engagement and response profiles as probabilistic, rather than deterministic, thus allowing the possibility of some random variation in responses. This is more attractive theoretically, positing that there can be measurement error in the way that the concept of engagement is captured with these items. But it is also useful practically, since it provides a way in which to arrange a large number of different response profiles into a smaller number of groups.

In the following analyses this approach is operationalised by means of latent class models (Lazarsfeld & Henry, 1968). Finding statistical associations between responses to the items described above, we infer that these associations are a function of some underlying, general variable characterising engagement. This general variable cannot be observed directly: it is a hypothesised latent variable, presumed to lie beneath the observed survey responses. In latent class models, the latent variable is categorical, and the observed items are typically also categorical. They may be treated as ordinal; or as in this paper, involving less strong assumptions, nominal.

The basic latent class model can be specified as follows:

x is a categorical latent variable, with q unordered categories $j=1,\ldots, q$; and

y_i $(i=1,...,p)$ are p observed or manifest variables, where y_i has c_i categories $s=1,..., c_i$.

We model the probabilities of belonging to class j:

$\eta_j = P(x=j), j=1,\ldots, q$

and the conditional response probabilities:

$\pi_{is}(j) = P(y_i=s|x=j)$,

that is, the probability of responding in category s to item i, given membership of latent class j.

These estimated conditional probabilities $\pi_{is}(j)$ are the key to interpreting any latent class model. For example, we might be interested in how the probability of being interested in science and technology 'most of the time' changes according to the latent class membership of a respondent. The content of the classes can be described by inspecting these conditional probabilities and looking for patterns – in simplest terms looking for high probabilities of giving certain sets of responses in each of the classes. When descriptions have been reached for the latent classes in a model, we might then be interested in the η_j, that is in the proportions of respondents expected to belong to each of them.

An alternative but equivalent way of presenting the model is to express $\pi_{is}(j)$ as a multinomial logistic regression model:

$$\log\left[\frac{\pi_{is}(j)}{\pi_{i1}(1)}\right] = \alpha_{i(1)}(s) + \sum_{\ell=2}^{q} \alpha_{i\ell}(s) x_\ell$$

where x_ℓ ($\ell = 2,\ldots,q$) are dummy variables representing the latent classes. This formulation is useful when describing cross-national models, where country is introduced as a covariate. In such a model the distribution of the latent variable (proportions in the classes) is allowed to vary between countries, but the aim is to fix the measurement model (the conditional item response probabilities) to be equal between countries. Where this can be done without compromising model fit too much, it should be possible to speak fairly confidently about a latent variable 'engagement' which is characterised in a broadly common way in all fifteen countries. Where such a model fits poorly, it can be informative to relax certain constraints on the measurement model. In this paper I give one simple example of this, allowing the conditional response probabilities (both intercepts $\alpha_{i1}(s)$, and slope parameters $\alpha_{i\ell}(s)$) for an item to vary by country – that is, specifying an interaction between latent variable, group (country) and item, as illustrated in Figure 1. Allowing the relationship between an item and its latent variable to vary by country implies that the item has a different interpretation among different countries in relation to the concept of engagement.

The models in this paper are implemented using Latent GOLD, version 4.0 (Vermunt & Magidson, 2005)[2]. One of the primary considerations in reaching a useful latent class model is deciding how many categories or classes are needed to fully represent the variation in the data. In the example described above, the answer must lie somewhere between one and eighty-one classes. A useful model must have a meaningful interpretation: that is, it should provide clear patterns of conditional response probabilities that allow us to characterise each of the classes in an unambiguous way. Fit statistics should also be used to aid model selection. In this paper some conventional fit statistics are presented: the likelihood ratio chi-squared statistic, L^2, number of degrees of freedom for the model and corresponding bootstrapped p-value (see Vermunt & Magidson, 2005); AIC; and BIC (e.g. Kuha, 2004). But model selection in this paper relies more heavily on inspection of two-way marginal residuals calculated from the models, following suggestions in Bartholomew, Steele, Moustaki, and Galbraith (2002), which draws on Bartholomew and Knott (1999) and Jöreskog and Moustaki (2001). For responses to each pair of items, a two-way marginal table is created, by collapsing over responses to the other variables. O, the observed frequency in a single cell of such a table, is then compared with E, the expected frequency for that same cell derived from the fitted model. The residual for each cell is calculated as $(O\text{-}E)^2/E$, that is, in standardised version, where values greater than four are taken to indicate poor fit (Bartholomew et al., 2002). The greater the number of large residuals, the worse the model is. In the models in this paper, the fit statistic used is the percentage of standardised marginal residuals greater than four.[3] A variant on this is also presented, under the heading 'Jöreskog and Moustaki index', based on Jöreskog and Moustaki (2001)[4]. In the models in this paper, a value of one or above on the Jöreskog and Moustaki index tends to indicate a very poorly fitting model.

In addition to the global statistics presented in the tables, in the text I document numbers of high marginal residuals for individual country-specific models. In selecting joint cross-national models, I also consider the percentage of high standardised marginal residuals conditional on country. These statistics are presented in full in Tables A.1 and A.2 in the Appendix to this paper.

The analyses that follow begin with latent class models applied separately to each country sample, and informal assessments of the similarities and differences in item functioning between countries. The models are then used to test, statistically, the extent to which the latent variable engagement can be characterised in a common way across country samples. This approach is straightforward, but absent from existing published analyses of PUS concepts. Latent variable models themselves are often used in cross-national analyses, but the common approach to their use is to pool the data from all countries – that is, treat the data as if they were sampled from a common population – and simply run the analysis for the total data set. This approach may often be justified, on theoretical or on empirical grounds – but sometimes it may be useful to question the assumption of a common population. The analyses in this paper address this very point, taking countries as separate populations, and explicitly investigating the question of whether the same latent variable representation of the construct engagement is found in different country samples.

Results

Affective and cognitive elements of engagement with science and technology

Three-class models fit well in most countries in the data set[5]. Table 3 gives an example of conditional response probabilities from one of these, for the UK data set. Notably high[6] probabilities are highlighted in grey. For example, conditional on membership in the first class in the table (looking at the first column of figures), a respondent has a 0.88 probability of saying he or she is interested in science and technology 'most of the time', a 0.72 probability of feeling well informed about science and technology 'most of the time', a 0.88 chance of claiming to understand science stories in the news 'most of the time' and a 0.56 chance of saying that he or she 'hardly ever' becomes confused when hearing conflicting views on science and technology. Given such a pattern of likely responses for people in this class we could characterise it as one of high engagement. This suggested label is included at the top of the column of figures, alongside other suggested labels for the other two classes. In the second class, the most likely response for every item is 'some of the time', whilst the last class may be characterised as one representing low engagement: respondents in this class are most likely to say they are interested, feel informed and understand science stories 'hardly any of the time', and become confused 'most of the time' when they hear conflicting views on science. The last row of the table gives the (unweighted) estimated probabilities of belonging in each class. For example, this model estimates that 22 per cent of the UK public would belong to the high engagement class[7].

It seems therefore that interest in science and technology tends to go hand in hand with confidence in one's grasp of the subject. However, the pattern is stronger for the first three items in the set, and weaker in relation to the last item. The more irregular functioning of the last item might be attributed to a variety of factors. In terms of the mechanics of the survey response process, it may be slightly more cognitively challenging simply by virtue of having a negative connotation, in contrast with the other items. In terms of substantive content, it may be logically linked to levels of engagement in a number of ways, making for some degree of heterogeneity in its meaning among respondents. For example, the statement is a non sequitur for respondents who are unexposed to conflicting views on science (making responses for this group error-prone), while exposed-but-detached respondents might hear conflicting views on science but remain nonchalant regarding their incompatibility, i.e. some of these unengaged respondents might answer in a way which we would take to denote high levels of engagement with the topic. By the same token, some highly engaged respondents may be more apt to become confused by conflicting views on science and technology; it may even be this confusion that motivates them to become better informed on the subject.

Inspecting the measurement models in these country-by-country analyses suggests that the last item is problematic generally. Table 4 presents a qualitative summary of the most likely responses in each class, for each country. This shows clearly that the first three items mirror each other consistently across countries, with very few exceptions, whereas the last item brings with it considerable variation. It is not just between countries that this item produces such heterogeneity of responses: within countries, conditional probabilities are generally much lower than for the other items. Indeed, even the most likely responses listed in the table are not very clearly defined. In light of the multiple possible interpretations of this question, it seems sensible to discard it at this stage. With the remaining three items, three-class solutions fit very well country-by-country[8], and qualitative inspections of most likely responses reveal exactly the same patterns as in the top half of Table 4.

Despite the similarities in response patterns across countries, a joint cross-national three-class model, with measurement model constrained to be equal across countries, fits poorly (Table 5). It seems that there is no single culprit item responsible for this, more a matter of the differences between countries in the relative magnitudes of the conditional probabilities for the three classes. The model does fit notably better in some countries than others, which might suggest that some clusters of countries share more similar measurement models in this regard. However, an informal inspection does not reveal any clear groupings, and exploratory statistical analyses do not shed any light on this idea. To investigate it, I ran some class models country-by-country, for just those respondents who do not give one of the three common sets of answers, to try to identify any patterns in these uncommon response profiles. These comprise approximately half of the sample in each country (ranging from 48 per cent in Ireland to 64 per cent in Greece and Finland). The analyses do not, however, help us to identify any groups of countries with similar sets of response profiles[9]. They suggest that it is not a systematic divergence in patterns in the data that accounts for the lack of fit of a three-class joint model. So there is no motivation to attempt to divide the data set into smaller sets of countries within which to fit models. An alternative, and for comparison purposes better strategy is to continue with the full fifteen-country data set, and simply increase the number of classes.

A seven-class solution is selected as a final model for these items, on the basis of fit statistics and interpretability. A six-class model, though apparently well fitting according to Table 5, does not return a very clear interpretation, and in fact gives cause for some concern in terms of numbers of large two-way marginal residuals. Although overall only 1.9 per cent of two-way residuals for a six-class model are large, conditional on country, rates are still very high in some instances; ranging from 3.7 in Austria to 29.6 per cent in Finland, with an average of 11.3 per cent among the fifteen countries. In a seven-class model, by contrast, they range from 0 in France, Portugal and Sweden, to 14.8 per cent in Belgium and Italy, but with an average across countries of just 5.9 per cent (see Tables A.1 and A.2 in the Appendix for full details). The patterns of conditional response probabilities are quite clear from this model, whereas an eighth class only serves to duplicate one of the classes from it. Seven classes are therefore retained.

A seven-class model returns an intuitively appealing set of classes (see Table 6). In between the primary classes of high, mid and low engagement (the first, middle and last columns in the table, labelled accordingly) there are two sets of two extra classes. So amongst those who say they are interested in science and technology 'most of the time', we can identify those who say that they however feel informed only 'some of the time' (high–), and those who further say that they understand science stories in the news only 'some of the time' (mid +). From the opposite end of the table, amongst those who say they feel informed about science and technology 'hardly any of the time, there are those who say they nevertheless understand science stories in the news 'some of the time' (low +) and those who say they are interested only 'some of the time' (mid –). So the classes can be thought of as grouped into three sets (mostly, sometimes and hardly) on the basis of the most usual response. For example, those classes under the heading 'sometimes' all imply a ‘some of the time’ response for two out of three items (albeit that this is only marginally true for the mid– group, and a different researcher might wish to classify it as a ‘hardly’ class).

Table 7 reports the percentages of respondents in each of the classes, by country and overall (recalculated from the final models using the sampling weights). The last three columns combine proportions into the three aggregated groups mostly, sometimes and hardly, and countries are ordered according to the total proportions in the first of these, i.e. the two high engagement classes. Across the fifteen countries overall approximately a third of the population are located at each level of engagement. Within Europe, however, these proportions vary markedly from country to country. With some notable exceptions, a broad pattern can be observed of higher rates of engagement with science in Scandinavian countries, and lower rates in southern European countries. For example, more than half of Swedes are predicted to be highly engaged, and only a quarter in the low engagement classes, whereas only 9 per cent of Portuguese are predicted to fall into the high engagement class, and the rest divided evenly between mid and low engagement. Looking a little more closely at these proportions, the detailed seven-column part of the table possibly suggests one of the reasons for the difficulty in achieving a well fitting joint model with a smaller number of classes. For some countries, no people are predicted to belong to certain classes – for example, no one in Luxembourg or Portugal is predicted to fall into the class high –, and likewise no one in the Netherlands or Germany is predicted to belong to the class mid +.

Behavioural elements of engagement with biotechnology

As a result of preliminary analyses, in this section I use a single item to represent exposure to biotechnology in the media, combining responses for all different types of media into one binary variable: having heard about biotechnology from any media source, versus not having heard about it from any source[10]. So there are four nominal variables to analyse.

Proceeding with the exploratory analyses, four-class models fit well within each of the fifteen countries[11]. Conditional probabilities for the example of the UK data set are presented in Table 8. In it we can identify a high engagement class, in which respondents are likely to have talked about biotechnology before and to have been exposed to biotechnology in some form of mass media in the last three months, and are likely to agree, in principle, to take part in public hearings on the topic, as well as to take time to read articles or watch television programmes about it. Next is a moderately engaged class, similar to the first but in which respondents are unlikely to want to take part in public discussions on the subject. Those in the mid–low engagement class are likely to answer negatively to all questions, except regarding reading an article or watching a programme about biotechnology, which they are marginally likely to be willing to do. Finally a low engagement and DK class represents those with profiles representing low engagement in terms of talking and hearing about biotechnology, and DK responses for the hypothetical participation questions.

The composition of these classes is not replicated straightforwardly in other countries, however. The qualitative summary of them given in Table 9 implies that fitting a cross-national model to these data will not be a straightforward matter. Although for each type of engagement there is a core of at least six countries which share broadly the same pattern of likely responses, there is a good deal of variation around these cores – moreover, the core group of countries changes in composition from class to class. Not every class group is found in every country, and in certain countries some types of classes are found twice. For example, there are two high engagement classes and no mid/mixed engagement class in Belgium, Finland and the UK. Likewise there are two low engagement classes and no mid/mixed engagement class in Ireland and Italy, and there are no DK classes in France or Spain. Although admittedly these claims rest on the judgement of the researcher in grouping responses patterns qualitatively, even a few changes to the classification would not change the overall verdict of considerable heterogeneity in measurement models between countries. Looking across the rows of the table, and looking down the columns of the table, it is not easy to pinpoint any particular source of this heterogeneity – it does not seem to be the case that one particular item or some particular countries are notably different from the others. So the analysis does not indicate that it would necessarily be helpful to test any particular interaction of item and latent variable; neither does it suggest any clusters of countries. It does clearly suggest, however, that a joint four-class model with measurement models constrained to be equal across countries will fit poorly.

Table 10 demonstrates that this is indeed the case. In the absence of any evidence from the qualitative analysis to suggest relaxing particular item parameters, increasing the number of classes is taken as a first step towards improving model fit. A six-class model returns a clearly interpretable measurement model, and as such is to be preferred over a seven-class model which, though better fitting statistically, contains two classes which are hard to define. In the six-class model, no item-by-item two-way marginal residuals are large, but conditional on country the average percentage of large residuals is 19.6, ranging from 0 in the Netherlands to 40.5 in Sweden (more information is given in the Appendix, Tables A.3 and A.4). From this point, since model fit is still quite poor, but increasing the number of classes does not seem to be fruitful, it is worth visiting the idea of testing for any notable improvements in model fit gained by freeing item parameters – specifically, allowing interactions between observed and latent variables. In the absence of a steer from the qualitative analyses, an interaction for each item is tested in turn. The greatest gain is achieved by allowing an interaction between the latent variable and one of the hypothetical behaviour questions, and all fit statistics suggest that freeing readtv brings a slight improvement in model fit over freeing discuss. In this final model, two-way marginal residuals are low overall, and conditional on country they range from 0 in Finland, Ireland, the Netherlands and Portugal, to 21.6 per cent in Denmark, with an average across countries of 5.8 per cent.

Table 11 gives patterns of conditional probabilities for the three items where the measurement model is constrained to be equal between countries. This shows that the two binary items asking respondents whether they have heard and talked about biotechnology mirror each other very closely. Within the two levels of these items we can clearly identify groups in each of the three possible response categories for the third item, expressing willingness to take part in a public discussion on the topic; agreeing and disagreeing, and responding DK.

Table 12 presents a qualitative summary to show how responses to the other 'willingness question', that is willingness to read articles or watch television programmes on biotechnology, varies between countries. In the table '+' indicates the response 'tend to agree', '–' denotes 'tend to disagree' and '?' is used where DK is the most likely response. Countries are ordered approximately according to the numbers of classes in which positive responses are expected, from the greatest number of positive classes to the least. Following a few unusually positive countries at the top of the table we can see a set – Belgium, Denmark, Ireland, Italy, the Netherlands and the UK – which follow the same pattern (this in fact is the profile that emerges from the six-class model where the measurement model is fixed to be equal between countries). According to this pattern, those in the 'low report' classes tend to make the same judgement on reading articles as on taking part in public discussions, while those in the 'high report' classes respond positively to this item, regardless of whether they would be willing to take part in discussions. It seems then that agreeing to take part in discussions on biotechnology is a more demanding item, or represents a higher bar in terms of levels of engagement, than reading articles and watching programmes on the topic. In the three countries at the top of the table, even those who have not heard or talked about the subject before and who would be unwilling to participate in discussion on it would still be willing to read about it, in principle. By contrast, in a few countries – those towards the bottom of the table – even in the high report classes, low willingness to discuss biotechnology goes hand in hand with low willingness to consume media on the subject.

Finally, Table 13 presents the proportions predicted to belong to each class (recalculated using sample weights). Countries are ordered according to proportions in the class representing the highest level of engagement. It is perhaps heartening for those working on public engagement with biotechnology that overall in the fifteen countries listed, more than half of the population is predicted to have heard and talked about biotechnology before, with nearly a third also willing in principle to take part in discussions on biotechnology and read articles or watch programmes about it. This enthusiasm varies by country, however. Whereas nearly half of the French belong to this keen group, only 13 per cent of Spaniards could be identified in the same way. In Spain, more than a third of the population is predicted to give a full negative set of responses, reporting not to have been exposed to biotechnology before and being unwilling to participate in learning or talking about it.

The ordering of countries approximately reflects that for engagement with science, though with a few exceptions – for example, Sweden appears somewhere in the middle of the list, on account of the fact that a high proportion of otherwise engaged respondents would prefer not to take part in public discussions on biotechnology (42 per cent belong to this high report, low willingness class, and just 23 per cent to the highest engagement class). The two DK classes are fairly sparsely populated overall, but with notably higher proportions in certain countries – for example, Italy, the Netherlands and Germany in the 'high report' class, and Ireland and Portugal in the 'low report' class. These exceptions to the general pattern might prompt us to ask whether they represent genuinely different levels of certainty in these countries, or whether they might be attributable to factors such as the questionnaire administration styles of the different survey organisations which conduct the fieldwork.

Discussion

The models presented above are not themselves ideal classifications of engagement: six- and seven-class models are perhaps a little larger than desirable, especially if they are to be used in analyses with other measures; and models involving interactions between item, latent variable and country compromise the cross-national comparability of the concept to some extent. However, for present purposes, they clearly demonstrate the utility of latent class models for exploring empirically-derived rather than prescriptively defined measures of a concept; for assessing item functioning in relation to the concept that an analyst wishes to measure; and for comparing item functioning between countries in order to assess the cross-national comparability of measures created.

As diagnostic tools on item functioning, the models provided very clear suggestions for two items in the data analysed. Amongst the science items, the statement 'I become confused when I hear conflicting views on science and technology' behaves irregularly in all countries, statistically speaking; a number of interpretations could be attributed to it – so for the purposes of developing a summary indicator of engagement with the other items, it would be expedient to drop it from future surveys. Among the biotechnology items, the statement 'I would be prepared to read articles or watch television programmes about biotechnology' is associated with the concept of engagement in notably different ways in different countries. Whilst this is informative in itself, it suggests that such an item is not an ideal candidate in a cross-national measure of engagement. A more general point deriving from this observation is that for cross-national measures, it would be useful for survey designers to review those items whose contents are clearly bound to countries' socio-economic climates and political histories. For example, the question asking if the respondent has heard about biotechnology on the internet is rather difficult to compare between countries where internet access is itself unevenly distributed. The culture for or against public meetings also varies markedly between European countries, making comparisons of the question, 'Would you attend a public hearing on biotechnology?' potentially difficult too.

Evening out the bases for comparisons is a useful general strategy when designing items for international surveys, even before any analysis begins. A strong message from the analyses carried out on these items – including many not presented here – is that the heterogeneity of the items makes the task of finding a cross-national model more difficult. The two sets of items between them contain a number of kinds of response formats, a number of possible response effects, and a number of types of content: affective and cognitive, reported behaviours and hypothetical willingness, sometimes in relation to science and technology in general, and sometimes to biotechnology in particular. Moreover, the items are dispersed throughout the questionnaire, rather than posed in a single battery. I could not find any well fitting cross-national model incorporating science and biotechnology items together, without specifying an unhelpfully large number of classes. A useful initial way to take these items forward into the next wave of the Eurobarometer would simply be to formulate a battery of ten or more questions, with the same or at least more similar question and response formats. In PUS the distinction between generalised and specific attitudes and knowledge is a matter of ongoing interest (see e.g. Allum, Sturgis, Tabourazi, & Brunton-Smith, 2008), but with the 2002 data set it is impossible to say whether there is a genuine separation between engagement with science and engagement with biotechnology, because the difference in item content is accompanied by a difference in item format.

The typologies of engagement presented in this paper are simply interpretations of statistical associations between questionnaire items, and as such I have consciously avoided drawing from them any deeper interpretations going beyond the statistical evidence in the data. Statistical models, by themselves, cannot tell us anything definitive about the meaning of a construct, as such, nor of the meaningfulness of comparisons made between countries or other groups. Qualitative and theoretically informed research is needed to answer questions on the full interpretation of a construct derived in a latent variable model. Nevertheless, statistical analyses can tell us whether in different samples the items tend to behave in the same way and tend to display similar patterns of associations. This, I would contend, is an important first step in sensitive comparative analyses, and is too often neglected. In this paper I hope to have usefully demonstrated one method for carrying it out, and to have highlighted some of the potential contributions of latent class models for this purpose.

Acknowledgements

I would like to thank Dr Jouni Kuha, Professor George Gaskell and Dr Niels Mejlgaard for their very helpful comments on this paper as it developed as part of my PhD research. In addition, I am very grateful to Dr Jouni Kuha for kindly writing several functions in S-PLUS software to deliver the model fit statistics which have played an important role in the analyses presented here.

Table 1 Distribution of responses to questions on engagement with science and technology; full European data set

Label	Statement	% responses*		
		Most of the time	Some of the time	Hardly any of the time
scint	I am interested in science and technology.	31	41	28
scinf	I feel well informed about science and technology.	18	44	38
scund	I understand science stories in the news.	30	45	25
scconf	I become confused when I hear conflicting views on science and technology.	25	44	27

n=15,837; 15,646; 15,710; 15,368

**Weighted frequencies, with countries' contributions to the tot*al weighted according to their population sizes. Totals do not always sum to 100 per cent due to rounding.

Table 2 Distribution of responses to questions on engagement with biotechnology; full European data set

Label	Statement	% responses*		
		Tend to agree	Tend to disagree	Don't know
discuss	I would be prepared to take part in public discussions or hearings about biotechnology.	33	53	15
readtv	I would take time to read articles or watch television programmes on the advantages and disadvantages of biotechnology.	68	23	9

n=16,040

		Yes, frequently	Yes, occasionally	Yes, only once or twice	No, never
talkbr	Before today have you ever talked about modern biotechnology with anyone?	6	27	17	50

n=15,786

	Before this interview, over the last three months, have you heard or read anything about issues involving modern biotechnology?	
heardbio	No.	41
npaper	Yes, in newspapers.	26
radio	Yes, on the radio.	10
mags	Yes, in magazines.	14
televis	Yes, on television.	39
www	Yes, on the internet.	3
forgot	Yes, does not remember where [spontaneous].	6

n=16,040

**Weighted frequencies, with countries' contributions to the total weighted according to their population sizes. Totals* do not always sum to 100 per cent due to rounding.

Table 3 Conditional and prior probabilities, 3-class latent class model for science items, example for UK sample data

Item	Response category	High engagement $\hat{\pi}_{is}(1)$	Middle responses $\hat{\pi}_{is}(2)$	Low engagement $\hat{\pi}_{is}(3)$
I am interested in science and technology	Hardly any of the time	0.02	0.11	0.87
	Some of the time	0.10	0.76	0.12
	Most of the time	0.88	0.14	0.02
I feel well informed about science and technology	Hardly any of the time	0.05	0.23	0.93
	Some of the time	0.23	0.74	0.05
	Most of the time	0.72	0.03	0.02
I understand science stories in the news	Hardly any of the time	0.00	0.11	0.72
	Some of the time	0.11	0.75	0.22
	Most of the time	0.88	0.14	0.05
I become confused when I hear conflicting views on science and technology	Hardly any of the time	0.56	0.20	0.22
	Some of the time	0.32	0.64	0.27
	Most of the time	0.12	0.15	0.51
$\hat{\eta}_j$	(unweighted)	0.22	0.39	0.39

Key

$\hat{\pi}_{is}(j)$ = estimated conditional probability of response in category s for item i, given membership of class j

$\hat{\eta}_j$ = estimated prior probability of membership in class j

Table 4 Qualitative summaries of highest conditional probabilities from unconstrained 3-class models, 15 countries

Items and countries	Classes and responses		
	High engagement	Middle responses	Low engagement
Interested			
All countries except…	Most	Some	Hardly
Greece	Most	Some/Most	Hardly
Informed			
All countries except…	Most	Some	Hardly
Finland	Most/Some	Some	Hardly
Understand			
All countries except…	Most	Some	Hardly
Denmark	Most	Some	Hardly/Some
Sweden	Most	Some	Some/Hardly
Become confused			
Ireland, Netherlands, UK	Hardly	Some	Most
Denmark, Sweden	Hardly	Some	Most/Some
Germany	Hardly	Some	Some/Most
Finland	Hardly	Some	Some/Hardly
Luxembourg	Hardly	Some	Hardly/Some
Austria	Hardly/Some	Some	Some/Most/Hardly
Greece, Portugal	Some/Hardly	Some	Most
Italy	Some	Some	Most
Spain	Some	Some	Most/Some/Hardly
Belgium	Some	Some	Hardly/Most
France	Some/Most	Some	Hardly/Most

Key

Most	Most of the time
Some	Some of the time
Hardly	Hardly any of the time

Table 5 Fit statistics for models of science items, with measurement models constrained to be equal across 15 countries

Model	L^2	d.f.	p (b'strap)	AIC	BIC	% 2-way standardised marginal residuals >4	Jöreskog & Moustaki index
3 classes	2,240	756	<0.001	728	-5,080	22.2	2.20
4 classes	1,844	735	<0.001	374	-5,273	16.0	1.50
5 classes	1,464	714	<0.001	36	-5,450	8.0	1.00
6 classes	1,210	693	<0.001	-176	-5,500	1.9	0.56
7 classes	1,041	672	<0.001	-303	-5,466	0.0	0.28

Table 6 Conditional probabilities, final 7-class model for science engagement

		Mostly		Sometimes			Hardly	
		High	High –	Mid +	Mid	Mid –	Low +	Low
Item	Response category	$\hat{\pi}_{is}(1)$	$\hat{\pi}_{is}(2)$	$\hat{\pi}_{is}(3)$	$\hat{\pi}_{is}(4)$	$\hat{\pi}_{is}(5)$	$\hat{\pi}_{is}(6)$	$\hat{\pi}_{is}(7)$
I am interested in science and technology	Hardly any of the time	0.01	0.02	0.00	0.10	0.00	0.58	0.91
	Some of the time	0.09	0.44	0.13	0.85	0.80	0.42	0.09
	Most of the time	0.90	0.54	0.87	0.06	0.19	0.00	0.00
I feel well informed about science and technology	Hardly any of the time	0.02	0.05	0.06	0.00	0.71	0.98	0.95
	Some of the time	0.07	0.95	0.81	0.96	0.29	0.01	0.04
	Most of the time	0.90	0.00	0.14	0.04	0.00	0.01	0.01
I understand science stories in the news	Hardly any of the time	0.01	0.02	0.03	0.06	0.47	0.02	0.90
	Some of the time	0.15	0.38	0.66	0.80	0.49	0.84	0.08
	Most of the time	0.84	0.60	0.31	0.14	0.04	0.14	0.02

Table 7 Weighted percentages of respondents in science engagement classes

% within country	Mostly		Sometimes			Hardly		TOTAL:	TOTAL:	TOTAL:
	High	High –	Mid +	Mid	Mid –	Low +	Low	MOSTLY	S'TIMES	HARDLY
Sweden	25	33	3	8	5	16	10	58	16	26
Netherlands	19	30	0	7	8	16	20	49	15	36
Italy	17	24	6	25	5	9	14	41	36	23
Denmark	29	11	2	29	0	14	15	41	31	29
Germany	22	17	0	26	2	16	17	39	28	33
Austria	21	7	5	26	5	13	23	28	36	36
Luxembourg	25	0	21	20	7	8	19	25	48	26
UK	18	7	3	23	6	13	30	25	32	43
Finland	11	10	14	13	19	15	18	20	46	34
France	15	2	17	23	17	5	21	17	57	26
Belgium	12	5	9	27	5	10	32	16	41	42
Spain	11	4	5	29	12	9	30	16	46	38
Greece	11	1	36	18	20	0	14	13	73	14
Ireland	9	1	7	25	6	14	39	10	38	52
Portugal	9	0	12	19	14	5	41	9	45	46
Europe total (pop. weighted)	17	12	7	24	8	11	22	29	38	33

Table 8 **Conditional and prior probabilities, 4-class latent class model for biotechnology items, example for UK sample data**

Item	Response	High $\hat{\pi}_{is}(1)$	High-mid $\hat{\pi}_{is}(2)$	Mid-low $\hat{\pi}_{is}(3)$	Low-DK $\hat{\pi}_{is}(4)$
Ever talked about biotech?	No	0.33	0.24	1.00	0.95
	Yes	0.67	0.76	0.00	0.05
Heard about biotech in last 3 months?	No	0.17	0.24	0.84	0.84
	Yes	0.83	0.76	0.16	0.16
Would take part in discussions or hearings.	DK	0.14	0.04	0.08	0.72
	Disagree	0.12	0.96	0.79	0.26
	Agree	0.74	0.00	0.13	0.02
Would watch TV programme or read articles.	DK	0.00	0.05	0.05	0.70
	Tend to disagree	0.04	0.22	0.45	0.03
	Tend to agree	0.96	0.73	0.50	0.28
$\hat{\eta}_j$	(unweighted)	0.30	0.20	0.44	0.07

Table 9 Qualitative summaries of conditional probabilities from unconstrained 4-class models, 15 countries

Classes and countries	Items and responses			
	Have talked about biotech (ever)	Have heard of biotech in media (in last three months)	Would take part in a discussion or hearing	Would read an article / watch a programme
High engagement				
Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Luxembourg, Netherlands, UK	Yes	Yes	Yes	Yes
Belgium, Italy, Portugal, Spain, Sweden, UK	Yes	Yes	No	Yes
Finland	No	Yes	Yes	Yes
Low engagement				
Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Portugal, Spain	No	No	No	No
Denmark, Netherlands, UK	No	No	No	Yes/No
France, Ireland, Sweden	No	No	No	Yes
Luxembourg	No	No	Yes/No	Yes
Luxembourg	No/Yes	Yes	No	No
Mid/mixed engagement				
Austria, Denmark, Germany, Greece, Portugal, Sweden	No	No	Yes	Yes
Italy	No	Yes	No	Yes
France	Yes	Yes	No	No
Netherlands	Yes/No	Yes	No	Yes/No
DK				
Austria, Belgium, Finland, Ireland, Italy, Portugal, Spain, UK	No	No	DK	DK
Germany, Netherlands	No	Yes	DK	DK
Spain	Yes	Yes	DK	DK
Denmark	Yes	No/Yes	DK/No	DK
Greece	No	No	DK	Yes
Luxembourg	No	Yes/No	DK	Yes
Sweden	Yes	Yes/No	No	Yes/DK

Table 10 Fit statistics for models of biotechnology items, with measurement models constrained to be equal across 15 countries

Model	L^2	d.f.	p (b'strap)	AIC	BIC	% 2-way standardised marginal residuals >4	Jöreskog & Moustaki index
Measurement model equal between countries							
4 classes	2,455	456	<0.001	1,543	-1,960	27.3	3.47
5 classes	1,649	435	<0.001	779	-2,563	18.2	1.40
6 classes	1,288	414	<0.001	460	-2,721	13.9	1.00
7 classes	1,032	393	<0.001	246	-2,773	7.5	0.62
6 classes, investigating interactions							
Interaction between talkbio and latent variable	866	330	<0.001	206	-2,329	6.4	0.44
Interaction between heardbio and latent variable	899	330	<0.001	239	-2,296	6.4	0.48
Interaction between discuss and latent variable	635	246	<0.001	143	-1,747	4.8	0.57
Interaction between readtv and latent variable	584	246	<0.001	92	-1,798	4.3	0.41

Table 11 **Final 6-class model for engagement with biotechnology, conditional probabilities for three items where measurement model is equal across countries**

		High report, high willingness	High report, low willingness	High report, DK willingness	Low report, high willingness	Low report, low willingness	Low report, DK willingness
Item	Response	$\hat{\pi}_{is}(1)$	$\hat{\pi}_{is}(2)$	$\hat{\pi}_{is}(3)$	$\hat{\pi}_{is}(4)$	$\hat{\pi}_{is}(5)$	$\hat{\pi}_{is}(6)$
Ever talked about biotech?	No	0.18	0.40	0.28	0.71	0.98	0.93
	Yes	0.82	0.60	0.72	0.29	0.02	0.07
Heard about biotech in last 3 months?	No	0.03	0.23	0.12	0.89	0.94	0.92
	Yes	0.97	0.77	0.88	0.11	0.06	0.08
Would take part in discussions or hearings.	DK	0.01	0.00	0.94	0.06	0.03	0.96
	Disagree	0.26	0.96	0.06	0.33	0.93	0.04
	Agree	0.73	0.04	0.00	0.61	0.04	0.01

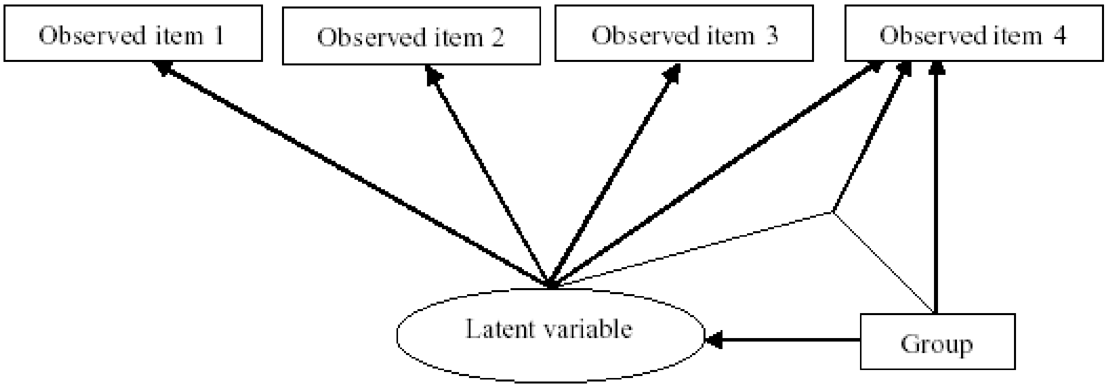
Table 12 **Final 6-class model for engagement with biotechnology, qualitative summary of highest conditional probabilities for fifteen countries, for the item ‘I would be prepared to read an article or watch a television programme about biotechnology’**

	High report, high willingness	High report, low willingness	High report, DK willingness	Low report, high willingness	Low report, low willingness	Low report, DK willingness
Sweden	+	+	+	+	+/–	?
Luxembourg	+	+	+	+	+/–	?/–
France	+	+/–	+	+	–/+	?/+
Belgium	+	+	+	+	–	?
Denmark	+	+	+	+	–	?
Ireland	+	+	+	+	–	?
Italy	+	+	+	+	–	?
Netherlands	+	+	+	+	–	?
UK	+	+	+	+	–	?
Greece	+	–	+	+	–/+	+/?
Austria	+	+/–	+	+	–	?
Finland	+	–/+	+	+	–	?
Germany	+	–	+	+	–	?
Portugal	+	–/+	?/+	+	–	?
Spain	+	+/–	?	+	–	?

Table 13 Weighted percentages of respondents in biotechnology engagement classes

% within country	High report, high willingness	High report, low willingness	High report, DK willingness	Low report, high willingness	Low report, low willingness	Low report, DK willingness
France	48	18	6	11	14	3
Luxembourg	42	22	4	20	10	2
Germany	41	16	12	19	8	3
Finland	40	26	5	15	11	3
Denmark	40	19	6	24	10	1
Netherlands	26	35	10	7	17	3
Austria	24	15	7	38	9	7
UK	23	20	5	13	32	7
Sweden	23	42	7	14	12	2
Ireland	23	15	6	18	26	12
Belgium	22	26	6	9	28	9
Italy	22	36	16	7	15	4
Greece	21	2	1	40	29	5
Portugal	16	14	4	31	24	12
Spain	13	30	8	5	36	7
Europe total (pop. weighted)	30	23	9	14	19	5

Figure 1 **Graphical depiction of an interaction effect between an observed item and latent variable**



Appendix Tables

Table A.1 Standardised residuals conditional on country for engagement with science and technology

Model	% 2-way standardised marginal residuals >4, conditional on country														
	Austria	Belgium	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Luxembourg	Netherlands	Portugal	Spain	Sweden	UK
Measurement model free to differ between countries															
4 items (scint, scinf, scund, sconf), 3 classes	1.9	5.6	1.9	11.1	3.7	5.6	1.9	5.6	3.7	1.9	7.4	0.0	1.9	3.7	5.6
3 items (scint, scinf, scund), 3 classes	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3 items, measurement model equal between countries															
3 classes	19	33.3	37.0	40.7	37.0	51.9	55.6	25.9	29.6	18.5	48.1	29.6	25.9	66.7	22.2
4 classes	14.8	18.5	25.9	33.3	25.9	37.0	40.7	22.2	33.3	7.4	44.4	29.6	18.5	59.3	11.1
5 classes	14.8	14.8	11.1	25.9	22.2	11.1	22.2	14.8	29.6	7.4	33.3	11.1	18.5	33.3	18.5
6 classes	3.7	18.5	3.7	29.6	11.1	14.8	22.2	11.1	14.8	7.4	7.4	3.7	3.7	7.4	11.1
7 classes	7.4	14.8	3.7	7.4	0.0	3.7	3.7	11.1	14.8	3.7	7.4	0.0	3.7	0.0	7.4
8 classes	14.8	0.0	0.0	0.0	0.0	0.0	3.7	7.4	0.0	0.0	0.0	3.7	0.0	0.0	7.4

Table A.2 Jöreskog & Moustaki index conditional on country for engagement with science and technology

	Jöreskog & Moustaki index, conditional on country														
	Austria	Belgium	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Luxembourg	Netherlands	Portugal	Spain	Sweden	UK
Measurement model free to differ between countries															
4 items (scint, scinf, scund, sconf), 3 classes	0.45	0.52	0.59	1.00	0.42	0.82	0.44	0.71	0.66	0.41	1.15	0.25	0.48	0.77	0.55
3 items (scint, scinf, scund), 3 classes	0.09	0.09	0.11	0.21	0.08	0.35	0.14	0.22	0.33	0.07	0.13	0.04	0.08	0.24	0.05
3 items, measurement model equal between countries															
3 classes	2.47	3.19	5.22	6.64	4.14	7.88	18.39	3.12	2.99	2.27	6.50	4.28	2.96	8.35	2.51
4 classes	1.80	2.91	3.92	5.88	3.61	5.13	5.42	2.65	2.91	1.59	6.45	3.68	2.02	7.82	1.41
5 classes	1.55	2.28	1.74	2.89	2.23	1.51	2.44	2.64	2.83	1.63	5.24	1.13	1.89	5.02	2.10
6 classes	1.04	2.11	1.15	2.54	1.41	1.41	2.30	1.92	1.60	1.23	1.31	0.51	1.27	1.20	1.35
7 classes	1.08	1.61	0.84	1.12	0.59	0.68	0.68	1.44	1.50	0.61	0.82	0.43	1.01	1.14	1.19
8 classes	0.48	1.22	0.55	1.01	0.63	0.75	0.76	1.18	0.72	0.53	0.60	0.53	1.05	0.82	1.03

Table A.3 Standardised residuals conditional on country for engagement with biotechnology

Model	% 2-way standardised marginal residuals >4, conditional on country														
	Austria	Belgium	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Luxembourg	Netherlands	Portugal	Spain	Sweden	UK
Measurement model free to differ between countries															
4 classes	0.0	0.0	0.0	0.0	2.7	2.7	0.0	0.0	2.7	0.0	0.0	0.0	5.4	0.0	2.7
Measurement model equal between countries															
4 classes	35.1	27.0	54.1	24.3	29.7	45.9	45.9	27.0	35.1	29.7	24.3	24.3	45.9	59.5	40.5
5 classes	32.4	24.3	37.8	18.9	18.9	32.4	13.5	13.5	21.6	24.3	5.4	27.0	32.4	43.2	35.1
6 classes	37.8	13.5	35.1	10.8	18.9	18.9	2.7	8.1	2.7	18.9	0.0	16.2	37.8	40.5	32.4
7 classes	27.0	13.5	32.4	0.0	18.9	5.4	0.0	8.1	10.8	21.6	0.0	0.0	18.9	21.6	13.5
6 classes, investigating interactions															
Interaction between talkbio and latent variable	35.1	5.4	5.4	10.8	5.4	10.8	0.0	10.8	0.0	5.4	0.0	10.8	27.0	35.1	8.1
Interaction between heardbio and latent variable	40.5	8.1	5.4	2.7	8.1	5.4	0.0	8.1	5.4	8.1	5.4	16.2	29.7	29.7	13.5
Interaction between discuss and latent variable	8.1	10.8	21.6	0.0	8.1	8.1	2.7	0.0	8.1	10.8	0.0	5.4	5.4	2.7	13.5
Interaction between readtv and latent variable	2.7	5.4	21.6	0.0	5.4	5.4	2.7	0.0	2.7	13.5	0.0	0.0	2.7	18.9	5.4

Table A.4 Jöreskog & Moustaki index conditional on country for engagement with biotechnology

	Jöreskog & Moustaki index, conditional on country														
	Austria	Belgium	Denmark	Finland	France	Germany	Greece	Ireland	Italy	Luxembourg	Netherlands	Portugal	Spain	Sweden	UK
Measurement model free to differ between countries															
4 classes	0.10	0.18	0.15	0.38	0.22	0.60	0.06	0.17	1.60	0.12	0.07	0.24	0.41	0.04	1.90
Measurement model equal between countries															
4 classes	5.61	3.69	7.96	2.99	3.83	6.20	6.46	3.59	8.41	3.84	2.72	3.44	6.37	12.31	4.54
5 classes	6.41	3.20	6.57	2.41	2.76	3.79	1.81	2.06	5.90	3.28	0.78	2.81	3.93	8.73	3.90
6 classes	6.92	2.42	6.09	1.54	2.72	2.16	0.93	1.22	1.81	2.51	0.69	1.98	4.31	9.15	3.79
7 classes	4.73	2.37	5.97	0.72	2.67	1.07	0.87	0.95	2.14	2.42	0.60	0.68	1.94	2.76	2.70
6 classes, investigating interactions															
Interaction between talkbio and latent variable	4.20	0.61	0.70	1.22	0.69	1.27	0.51	1.22	0.54	0.48	0.48	1.65	2.36	5.99	1.49
Interaction between heardbio and latent variable	5.82	1.01	0.76	0.92	0.90	0.74	0.26	1.10	0.77	0.54	0.77	2.25	2.59	4.60	1.58
Interaction between discuss and latent variable	2.53	1.56	4.97	0.17	1.90	1.22	0.57	0.35	1.91	1.51	0.39	0.57	0.95	1.83	2.29
Interaction between readtv and latent variable	0.96	1.31	5.25	0.25	1.18	0.77	0.58	0.22	1.44	1.80	0.17	0.40	0.62	2.75	1.70

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[1] The most commonly used items are sets of statements about science and technology which respondents are asked to identify as true or false. Examples of them may be found in Eurobarometer surveys such as the one analysed in this paper; they may also be found in the many surveys run by the National Science Foundation in the US.

[2] For transparency, a few essential details should be noted regarding the specification used within this software. Firstly, by default Latent GOLD specifies a prior distribution for the latent and conditional response probabilities – ‘Bayes constants’ in Latent GOLD terminology – to avoid boundary solutions, that is estimated probabilities of 0 or 1. The default values in Latent GOLD are vague priors, so the estimates from models using these differ little from Maximum

Likelihood estimates. Secondly, to counter the possibility of iterations converging to a local rather than a global maximum of the likelihood function, each estimation run begins with one hundred sets of random starting values, from which the best is chosen automatically by the software to calculate model parameter estimates. The third detail regards weighting. The main bulk of the analysis is carried out on an unweighted data set. However, in the final joint cross-national latent class models presented in this paper, the models have been re-estimated applying a two-step weighting procedure available in Latent GOLD and recommended by the authors of the programme (see Vermunt & Magidson, 2005, for details). The estimated prior probabilities of membership in each class are given for each country, applying the basic case-level weights provided in the original survey data set, and for the fifteen EU countries together, weighted according to their relative population sizes. The last technical detail regards the treatment of missing responses. With the 'biotechnology' items there are no missing responses; 'don't know' responses are simply treated as an extra category of nominal variables. For the 'science' items, because the rates of 'don't know' responses are very low, they are treated as missing, but to avoid listwise deletion of response profiles containing 'don't know' responses for these items, Full Information Maximum Likelihood estimation is used when fitting the latent class models.

[3] These statistics are calculated using functions kindly written by Dr Jouni Kuha, in S-PLUS software. Margins involving one or more missing ('don't know') response are not included in the calculation of these statistics.

[4] In this approach I sum the two-way marginal residuals for pairs of items, for all categories of those items. So, where m denotes the number of response categories for an item, for items i and j I calculate the sum, S_{ij}, of all two-way standardised marginal residuals in the (m_i*m_j) table. To take into account differing rates of m, this is converted into a common metric using $S_{ij}/(m_i*m_j)$. Then to reach a single figure to summarise the information for a model, this is repeated for all combinations of pairs of items, and the mean of all the $S_{ij}/(m_i*m_j)$ is taken as the final measure of goodness of fit.

[5] The percentage of standardised marginal residuals > 4 is on average 4.1 across countries, with a range of 0.0 in Portugal to 11.1 in Finland.

[6] In general, conditional probabilities of 0.4 or greater are highlighted in grey. This arbitrary rule of thumb derives from observations during analyses that where one conditional response for an item is greater than 0.4, other responses tend to have low probabilities of occurring.

[7] These are unweighted probabilities, as indicated in the table. In the final models presented in the paper, the models were refitted with these statistics adjusted, to reflect sampling weights, as described in Note 2. In practice these weights make very little difference to the estimated prior probabilities, and no difference to the measurement models, so the estimates are left unweighted for the interim models.

[8] For every country, no standardised marginal residuals > 4.

[9] With three-class models, amongst the fifteen countries seven different types of class emerge, and with four-class models, ten different types. Amongst these classes, some countries seem to share a similar set of classes, but these tend to be only pairs or trios of countries. Moreover these apparent groupings are quite unstable, and alter in composition when the models are changed from three-class to four-class.

[10] These preliminary analyses lent support to my initial supposition – that different cross-national baseline rates of access to different forms of media would create problems for finding a joint cross-national model, if they were treated as separate items.

[11] The percentage of standardised marginal residuals > 4 is on average 1.1 across countries, with 0 in ten countries, up to 5.4 in Spain.