Predictors of Science Achievement in PISA (2006): Collaborating in a Community of Practice to Build Capacity in Analyses Using HLM

Abstract

Hierarchical linear modeling was used to investigate the relationship between student and school background variables and student achievement on the 2006 OECD Programme for International Student Assessment (PISA) science assessment of 15-year-olds. Over 3,000 Ontario students from 130 English- and French-language schools participated in PISA; the students are clustered by school in the analyses. In addition to discussing statistical findings, we will also discuss the usefulness of HLM for this type of analysis and the challenges and lessons learned in building capacity for the analysis, interpreting the results, and drawing useful conclusions.

Introduction

The present study examines the 2006 OECD Programme for International Student Assessment (PISA) science achievement data of 15-year-olds in Ontario. First, we will discuss the results and an interpretation of our analyses. Secondly, we will discuss our process in analyzing the data, including the challenges and lessons learned in building our own capacity in analysis using Hierarchical Linear Modeling, and interpretation of the results.

Since 2000, the Programme for International Student Assessment (PISA) has been administered internationally by the Organisation for Economic Co-operation and Development (OECD) every three years to 15-year-olds enrolled in schools. Each iteration focuses on one of three areas: literacy, mathematics literacy, and science
literacy. In 2006, the focus was on science literacy and as this was the most recent dataset available, we chose this for our analyses.

PISA assesses the ability to apply science learning in real-world situations, as well as the attitudes, values and beliefs students have about science. The present study explores both of these areas. PISA also collects family background information (e.g. an index of economic, social and cultural status), which we also included, since a significant relationship has been demonstrated between family sociodemographic factors and student performance across all countries that participated in the PISA assessment (Willms, 2005).

Although fifty-seven countries participated in the 2006 PISA assessment, we were specifically interested in the results for Ontario because no literature exists for the subset of Ontario students. Further, the HLM Learning and Research Community that supported this study is an Ontario group interested in student achievement results in Ontario schools.

The research examining factors influencing students’ science literacy achievement is limited. International studies have explored science literacy achievement using the 2006 PISA dataset. In a Scandinavian study, researchers explored the similarities and differences between the Nordic countries in gender-specific scientific literacy scores, conceptual (scientific concepts) and intellectual processing skills (scientific reasoning) (Kjaernsli & Lie, 2004). Results demonstrated that the Nordic countries vary in the magnitude of the gender differences in science achievement, with the greatest relative advantage for boys in Denmark compared to the other Nordic countries (Kjaernsli & Lie, 2004). Similarly, there were no common Nordic patterns demonstrated in the data on students’ relative strengths in processing skills or conceptual understanding (Kjaernsli &
This highlights how relative proximity between countries does not necessarily imply similar correlates of student achievement, and is an argument for why we are interested specifically in examining the Ontario science literacy data. In New Zealand, researchers investigated the applications of the PISA study and the International Mathematics and Science Study (TIMS) to practice and policy, and made recommendations for future research in science education (Baker & Jones, 2005).

Researchers reviewed studies that examined the correlates of student achievement, including gender, socio-economic factors, and teacher and school factors. This highlights the importance of including demographic variables, and accounting for school factors in examining predictors of science achievement. A Canadian study that examined the 2003 PISA data examined the extent to which socioeconomic background, gender and region are sources of educational inequality in Canada. The results demonstrated the link between socioeconomic background, gender and region, and further emphasize the importance of accounting for demographic variables in examining predictors of science achievement in the Canadian context (Edgerton, Peter, & Roberts, 2009).

Another important consideration in examining student achievement is home supports for learning. Studies have demonstrated the importance of family involvement in children’s school success (Epstein, Coates, Salinas, Saunders, & Simon, 1997; Snow, Burns, & Griffin, 1998). Epstein (1995) describes six types of parental (family) involvement: learning at home, parenting, communicating, volunteering, decision-making, and collaborating with the community (Epstein, 1995). Supporting learning at home can include home educational resources, which is measured by the PISA (2006) student survey. In the PISA (2006) student survey, home educational resources include a
desk to study at, a quiet place to study, a computer you can use for school work, link to the internet, a calculator, among others. Providing access to home educational resources is likely to be a priority for any family which values education, irrespective of their socioeconomic status.

In the Hierarchical Linear Modeling Learning and Research Community (HLM-LRC), we were able to engage in knowledge building to improve and share ideas for the application of statistical techniques to our respective community, university, and government settings. This was facilitated through our participation in a “community of practice” (Wenger, 2001). A community of practice is a group of people who share a common enthusiasm or concern about a topic, and who deepen their expertise and knowledge by interacting on an ongoing basis (Snyder, Wenger, & Briggs, 2004). In a community of practice, professionals connect to develop relationships with peers and stakeholders, solve problems, build tools together, share ideas, and act on a common passion regarding a particular practice domain (Patel, Corter, & Pelletier, 2008). This study is an initiative of a community of practice that included professionals in community school boards, university, and government settings, who share common goals of using Hierarchical Linear Modeling to analyze student achievement results in educational settings across Ontario.

According to Wenger (2004), the most successful communities of practice “have always combined bottom-up enthusiasm and initiative from members with top-down encouragement from the organization” (p. 6). The effectiveness of a community of practice depends on the strength of three structural dimensions of the community (Wenger, 2000): the domain (focal issue), the community (quality of
relationships/interactions between members), and practice (repertoire of tools, methods, and learning and innovation activities). Professionals need to form communities in their own domain, and then mutual engagement needs to be supported through a process of practice development, not simply one-shot brown bag lunches about a topic or issue (Wenger, 2004). If a new solution is proposed in a practice community, professionals can apply the lessons learned to their own work and vice versa; if a new solution is discovered by a community member in their work, they can share it with the community of practice (Wenger, 2004). An important goal of a community of practice is dissemination; lessons learned and best practices that arise from the work of a community of practice should be shared (Wenger, 2004).

Through our participation in the Hierarchical Linear Modeling Learning and Research Community, we were able to engage in knowledge building within the context of a community of practice. This innovative approach to inter-agency collaboration brought together representatives of community school boards, universities and the government.

In this presentation, we will share the results of our mutual efforts. First, we will discuss the results of our joint analyses of the 2006 OECD Programme for International Student Assessment (PISA) student science achievement data. Secondly, we will share our experience, challenges and lessons learned in engaging in inter-agency collaboration within the context of the Hierarchical Linear Modeling Learning and Research Community.

The present study aims to answer the following research questions:
(1) Which student characteristics and school factors from PISA (2006) predicted the science literacy achievement of students in Ontario?

♦ Do schools (i.e., school activities to promote the learning of science, quality of educational resources, school size) influence science achievement, above and beyond student characteristics (i.e., science efficacy, future-oriented science orientation, joy of science, gender), and while accounting for family sociodemographic characteristics (i.e., economic, social and cultural status)?
♦ Do students’ home educational resources influence science achievement, above and beyond other student and school characteristics?

(2) What did we learn from our collaborative efforts in building capacity to use HLM to analyse data?

♦ What are the challenges and lessons learned in building our readiness and capacity for reaching the analysis stage, interpreting the results, and drawing useful conclusions as a learning exercise in a community of practice?

Methods

(1) Which student characteristics and school factors from PISA (2006) predicted the science literacy achievement of students in Ontario?

The present study analyzed PISA science literacy data for 3051 students nested in 130 Ontario schools using Hierarchical Linear Modeling (Raudenbush & Bryk, 2002). The sample includes both English and French, public and private schools. Students ranged in age from 15.3 to 16.3, with a mean age of 15.8 years. Almost one quarter of the sample (23.6%) included at least one parent who reported having a science-related career. Examples of careers coded as science-related in PISA (2006) include, research and...
development positions, health professionals, social work professionals, computing professionals, engineers, physicists, statisticians, sociologists, psychologists, and air traffic pilots, among others (OECD, 2009). In examining the highest level of parental education, 19.0% of parents had an upper secondary or non-tertiary post-secondary education level (12 years of schooling), 28.0% had a vocational tertiary education level (15 years of schooling), and 40.2% reported having a theoretically oriented tertiary and post-graduate education level of schooling (17 years of schooling), with 10.3% missing data. Over one quarter (27.4%) of the mothers were born in a country other than Canada, with 60.7% born in Canada, and 11.9% missing data. The school sample included 88.5% public schools, and 3.1% private schools, with 8.5% missing data. The average teacher-student ratio in these schools was 1 teacher for every 16 students. The PISA data (see http://pisa200.acer.edu.au/downloads.php) were chosen for our analysis because these data provide rich information on a range of factors that may be influential in Ontario students’ science achievement.

Student-level and school-level datasets that contain data from the Student and School Questionnaires for PISA 2006 were downloaded from the OECD website. Using Provincial identifier codes provided by Statistics Canada, we extracted Ontario-specific data for our student- and school-level datasets. The datasets were prepared using SPSS, Version 17.0 and were imported into the Hierarchical Linear and Nonlinear Modeling computer program (HLM Version 6.0.2., Raudenbush & Bryk, 2002).

In order to select variables to include as possible predictors in our model, we conducted frequency, descriptive, and correlational statistical analyses. In addition, we dummy coded the gender variable such that female=0, male=1. All prospective variables
were tested for multicollinearity. Further, possible theoretical reasons for variable inclusion were explored. We collaborated, shared thoughts on plausible models, and came to a final model predicting PISA science achievement (the first plausible value, PV1SCIE was used as the science achievement score). We included a student weight variable in the HLM analyses (W_FSTUWT) to account for the sampling design that was used by Statistics Canada to select the schools. The final model included the following variables:

**Dependent Variable:**

- Student Science Achievement (PV1SCIE)

The science achievement scores ranged from 205.55 to 834.97, with a mean of 522.94 and a standard deviation of 94.37.

**At the student level (Level 1):**

- School ID (ID variable)
- science efficacy (SCIEFF)
- future-oriented science orientation (SCIFUT)
- joy of science (JOYSCIE)
- home educational resources (HEDRES)
- index of economic, social and cultural status (ESCS)
- gender (GENDER)

Please see Table 1 for detailed descriptive statistics of the continuous independent variables at the student-level.
Table 1

Descriptives of Level 1 Continuous Independent Variables

<table>
<thead>
<tr>
<th>Variable Description</th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Home educational resources PISA 2006 (WLE)</td>
<td>2756</td>
<td>-4.1263</td>
<td>.7190</td>
<td>.093197</td>
<td>.8016823</td>
</tr>
<tr>
<td>Enjoyment of science PISA 2006 (WLE)</td>
<td>2754</td>
<td>-2.1517</td>
<td>2.0562</td>
<td>.178861</td>
<td>1.0417958</td>
</tr>
<tr>
<td>Science self-efficacy PISA 2006 (WLE)</td>
<td>2744</td>
<td>-3.7682</td>
<td>3.2230</td>
<td>.248679</td>
<td>1.0568647</td>
</tr>
<tr>
<td>Future-oriented science motivation PISA 2006 (WLE)</td>
<td>2742</td>
<td>-1.4186</td>
<td>2.2714</td>
<td>.303954</td>
<td>1.1029508</td>
</tr>
<tr>
<td>Index of economic, social and cultural status PISA 2006</td>
<td>2750</td>
<td>-3.1637</td>
<td>2.6767</td>
<td>.461780</td>
<td>.7884912</td>
</tr>
</tbody>
</table>

In addition to the variables listed in Table 1, there was one categorical independent variable, gender, entered at the student level. In the study sample, there were equal proportions of females (N=1525) and males (N=1526).

At the school level (Level 2):

♦ School ID (ID variable)

♦ school activities to promote the learning of science (SCIPROM)

♦ school size (SCHSIZE)

♦ quality of educational resources (SCMATEDU)

Please see Table 2 for detailed descriptive statistics of the independent variables (all continuous) at the school-level.
Table 2

Descriptives of Level 2 Continuous Independent Variables

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>School size</td>
<td>108</td>
<td>65</td>
<td>2185</td>
<td>913.39</td>
<td>498.194</td>
</tr>
<tr>
<td>School activities to promote the learning of science PISA 2006 (WLE)</td>
<td>117</td>
<td>-2.2697</td>
<td>1.6397</td>
<td>0.391859</td>
<td>0.9903491</td>
</tr>
<tr>
<td>Quality of educational resources PISA 2006 (WLE)</td>
<td>116</td>
<td>-2.6388</td>
<td>2.1351</td>
<td>-0.011841</td>
<td>0.9667036</td>
</tr>
</tbody>
</table>

Variables entered at Level 1 were group mean centered, with the exception of ‘gender’, which was uncentered as it is a binary variable. Group mean centering enables interpretation of the intercept relative to the groups and not relative to the overall mean (Raudenbush & Bryk, 2002), which is most appropriate for these analyses. At Level 2, we used grand mean centering instead, as this is the most recommended approach for Level 2 variables (Raudenbush & Bryk, 2002). School ID was entered as an identifying variable to link the student level and school level data in HLM. Since we had no reason to believe that the slopes would vary among schools, analyses were conducted using fixed effects.

(2) What did we learn from our collaborative efforts in building capacity to use HLM to analyse data?

Daria Lysy, Ruth Childs, Barnabas Emenogu and Sejal Patel collaborated on the PISA project. Daria Lysy is a Senior Statistical Research Analyst with the Ministry of Education, in the Student Success/Learning to 18 Implementation, Training and Evaluation branch. Ruth Childs is a Professor in the Department of Human Development and Applied Psychology at the Ontario Institute for Studies in Education of the University of Toronto (OISE/UT). Barnabas Emenogu is a Senior Research Coordinator at the Literacy and Numeracy Secretariat at the Ministry of Education. Sejal Patel is a
doctoral candidate in the Department of Human Development and Applied Psychology at OISE/UT and the Research Manager of the Toronto First Duty Research and Development Team of the Atkinson Centre (Institute of Child Study). Both Daria and Sejal audited a course on Hierarchical Linear Modeling taught at OISEUT.

Ruth mentored Daria and Sejal through setting up the data file for analysis, by helping connect them with the necessary ON Provincial codes, and by helping to get them started. Daria’s approach involved starting specifically with an examination of the data first to examine frequencies, distributions and correlations in order to determine which predictors to include in her proposed multi-level model. Sejal’s approach involved a more theoretical inclination, starting first by thinking about possible theoretical contributors to science achievement, and examining the correlation matrix thereafter. We combined our approaches to come together collaboratively with our final model, as described above. Barnabas was very helpful in trouble shooting as we worked through the analyses in HLM.

**Results**

(1) *Which student characteristics and school factors from PISA (2006) predicted the science literacy achievement of students in Ontario?*

Table 3 shows the means and standard deviations of the outcome and predictor variables, as well as coding information for the dichotomous variable (gender).
Table 3
Means and Standard Deviations of Outcome and Predictor Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Student achievement (Outcome variable)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Science</td>
<td>522.93</td>
<td>94.37</td>
</tr>
<tr>
<td>Level 1/Student characteristics (Predictor variables)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender (0=male; 1=female)</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>Science efficacy</td>
<td>0.25</td>
<td>1.06</td>
</tr>
<tr>
<td>Future-oriented science orientation</td>
<td>0.30</td>
<td>1.10</td>
</tr>
<tr>
<td>Joy of science</td>
<td>0.18</td>
<td>1.04</td>
</tr>
<tr>
<td>Home educational resources</td>
<td>0.09</td>
<td>0.80</td>
</tr>
<tr>
<td>Index of economic, social and cultural status</td>
<td>0.46</td>
<td>0.79</td>
</tr>
<tr>
<td>Level 2/School characteristics (Predictor variables)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>School size</td>
<td>768.01</td>
<td>517.25</td>
</tr>
<tr>
<td>School activities to promote the learning of science</td>
<td>0.25</td>
<td>0.96</td>
</tr>
<tr>
<td>Quality of educational resources</td>
<td>0.05</td>
<td>0.96</td>
</tr>
</tbody>
</table>

All of the variation in achievement was due to student-level characteristics, that is, among students within schools. None of our school predictors were significant. Of the student-level predictors, joy of science ($\beta=+13.93$), science efficacy ($\beta=+27.67$), and the index of economic, cultural, and social status ($\beta=+13.85$) were each significant. Contrary to international studies examining the PISA data, gender was not a significant predictor of student science achievement. Further, home educational resources were not a significant predictor of student science achievement. Together, all of the student-level predictors accounted for 22% of the variance in our outcome variable of science achievement.

2. What did we learn from our collaborative efforts in building capacity to use HLM to analyze data?

Through the unique experience of participating in the Hierarchical Linear Modeling Learning and Research Community, we were able to work collaboratively through community, university, and government partnerships. By participating in this community of practice, we were able to cross boundaries within and between our respective organizations to engage in interdisciplinary knowledge building (i.e. Patel,
Corter, & Pelletier, 2008). We were able to engage directly with colleagues who would otherwise work more exclusively in their own silos and professional circles. By collaborating, we more efficiently overcame many challenges along the way, including resolving issues of data access, getting access to relevant literature, working with ‘weighted’ data, and negotiating between different approaches to data analyses to come to a final coherent model, among others. Through the HLM-LRC we shared our lessons learned, problem solving approaches, and the challenges we faced along the way.

**Overview and Conclusions**

This study found that a total of 22% of the variance in students’ science achievement outcomes is attributable to student level predictors, including students’ science efficacy, or belief that they can do well in science, students’ enjoyment of science, and their socioeconomic status. Interestingly, we found that home educational resources do not predict students’ science achievement above and beyond other student and school characteristics. Further, through this unique collaborative opportunity to participate as members of a community of practice, we were able to build our capacity in the use of hierarchical linear modeling and are able to apply these skills to our own professional settings. In light of the call for data-based decision-making to help guide instructional and educational policy decisions ultimately leading to system improvement and growth (Klinger, Rogers, Anderson, Poth, & Calman, 2006), it is imperative that communities, governments and academic institutions come together to build capacity in and trouble shoot around the modern statistical techniques necessary to analyze large-scale and community level assessment data. Partnership development between
communities, governments and academic institutions is an emerging approach that holds promise for improving outcomes for children (Taylor, Beane, & Genee, 1998).
References


