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Home resources as a measure of socio-economic status in Ghana

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Abstract

In large scale international assessment studies, questionnaires are typical used to query students' home possessions. Composite scores are computed from responses to the home resource questionnaires and are used as a measure of family socioeconomic background in achievement comparison or for statistical control. This paper deals with profiling the socio-economic status (SES) of Ghanaian students' in the context of the TIMSS 2011 study. Latent class analysis was used to profile students into respective SES classes based on the students' responses to 11 questions concerning their home resources. The results showed three clearly distinct socio-economic profiles: high-, middle- and low-SES. Moreover, a discriminate analysis was conducted to explore the degree to which the groups are accurately classified. The discriminant analysis was able to correctly classify 92.20% of the individual students into their appropriate SES group. A gender comparison of these classes suggested stable measurement invariance for the latent class indicators. This article contributes to addressing the composition of SES by providing statistical criteria to evaluate SES using empirical data.

Keywords: TIMSS, Ghana, Socio-economic status/profiles, Latent class analysis, Discriminant analysis, Home possessions/resources

Introduction

Ghana is a sub-Saharan African country with a medium-level human development index, placing it above the regional average (United Nations Development Programme 2013). In Ghana, children can be from vastly different cultures, and have very different backgrounds experiences. Quality education for all students has been the main objective of most policymakers; however, years of research have shown that family socioeconomic status indicates the available educational opportunities (e.g., Aikens and Barbarin 2008; Parker et al. 2012; Siegler 2009). For instance, according to UNESCO's Education for All Global Monitoring Report 2015, one in six children in low- and middle income countries will not complete primary school in 2015 (UNESCO 2015). In Ghana, for example, 87% of students from low socioeconomic homes enter primary school, but only 72% graduates, compare to 100% enrolment for children from high socioeconomic homes, of which 80% graduates. Moreover, 60% of children from low socioeconomic homes enter primary school at least two years older than the official age, compared to 32% of children from high socioeconomic homes (UNESCO 2013).

Research on the link between achievement and Socio-economic status (hereinafter SES) has consistently indicated that students from high socioeconomic backgrounds have higher academic achievement than their peers from low socioeconomic backgrounds (Bofah 2015; Erberber et al. 2015; Jurdak 2014; Sirin 2005; Wang et al. 2014). The association between higher SES and achievement is universal across nations, school subjects (e.g., mathematics and science), and grades (e.g., from primary to secondary education) (Bofah 2015; Erberber et al. 2015; Martin et al. 2012; Mullis et al. 2012; OCED 2011).

Although it is well documented that students from low-SES backgrounds perform below expectation, studies have shown that some are academically successful despite their challenging backgrounds (Erberber et al. 2015; OCED 2011). For example, in the Trends in International Mathematics and Science (TIMSS 2011) study, Ghana reported the highest percentage of students from low-income homes, of whom 4% scored above the *Intermediate International mathematic Benchmark* (475) (Erberber et al. 2015).

Using latent class analysis (LCA) (Goodman 1974; Lazarsfeld and Henry 1968), we classify students into socioeconomic groups based on their responses to questions concerning 11 household items from the TIMSS 2011 study. Due to the impact of socioeconomic background on educational achievement, our study draws on theories from other academic discipline, and focuses on a question of broad importance: To what extent can home possessions be used to profile students' SES?

Background

SES has been the most widely used latent construct for measuring family background. The SES concept encompasses many variables (Filmer and Pritchett 1999; Hauser and Warren 1996; Hauser 1994; Ormrod 2011; Schulz 2005), but the most common indicators of SES include parental education, parental occupation; family income/wealth, and prestige; home literacy resources; and certain activities such as participation in social, cultural, or political life (Buchmann 2002; Hauser and Warren 1996; House 1981; Mueller and Parcel 1981; Schulz 2005). Other indicators include tangible possessions such as houses, cars, boats, appliances, and digital equipment (Hauser and Warren 1996; Park 2008; Xu and Hampden-Thompson 2012).

High-SES background is positively associated with educational outcomes in addition, subtraction, ordinal sequencing, and numeracy, as well as mathematics word problems (Coley 2002; Siegler 2009), cognitive development (Paxson and Schady 2007; Yeung and Conley 2008), language development (Fernald et al. 2013; Hoff 2003), educational choices (Parker et al. 2012), achievement (Bofah 2015; Erberber et al. 2015; Jurdak 2014; Kupari and Nissinen 2013; Michaelowa et al. 2001; Mullis et al. 2012; Sirin 2005; Wang et al. 2014; Williams and Williams 2010), mathematics-related affect (Bofah 2015, 2016; Hannula et al. 2014; Williams and Williams 2010) and attainment (Filmer and Pritchett 1999; Teachman 1987; UNESCO 2013).

Studies have shown that SES shapes children's language learning environments and their language development (Fernald et al. 2013; Hoff 2003). Hoff (2003) found that language development such as lexical richness of speech produced in conversation differ by SES, and that SES shapes children's language learning environments and influences the development of their language. Fernald and colleagues, found a significant disparities in vocabulary and language processing efficiency to be already evident at 18 months between infants from higher- and lower-SES families, and by 24 months there was a six-month gap between SES groups in processing skills critical to language development.

Moreover, lower parental involvement (e.g., parent–child communication and parent–child discussion) (McNeal 1999; Park 2008), school absenteeism, enrollment and dropout (Langhout et al. 2009; McKenzie 2005; National Center for Education Statistics 2008; Zhang 2003), as well as poor teacher quality (Akiba et al. 2007) are associated with students from low-SES families. This is explained by such families often having limited financial resources, which restrict their ability to provide their children with learning materials such as books and computers (Orr 2003), and consequently a cognitively stimulating learning environment (Klebanov et al. 1994; Orr 2003; Yeung et al. 2002).

The relationship between parental involvement and SES has been found to be culturally specific (Desimone 1999; McNeal 1999; Park 2008). For instance, in some countries high-SES students' may benefit from parent–child communication, while in others they may benefit from other forms of parental involvement such as help with homework. In Ghana, a common phenomenon among high-SES parents who wish to support their children education is to hire a private home-tutor or send the child to extra lessons after the normal school day. However, the literature indicates that middle- and high-SES parents are more likely to participate in their children's educational activities compared to their peers from low-SES backgrounds (e.g., Coley 2002; Teachman et al. 1997). McNeal (1999) found that parental-child discussion was significantly lower in low-SES than high-SES homes. Park (2008) found that parent–child communication is greater for high-SES than low-SES students. Moreover, "this greater parental participation, support and investment in their children's education is driven by the recognition that educational success is the main route for reproducing their class status" (Perry 2012, p. 22).

Children who live and are educated in vicinities with well-financed schools are more likely to have higher educational aspirations (Madarasova Geckova et al. 2010; Teachman and Paasch 1998), and numerous studies have indicated that family SES influences the educational aspirations of the children (Bowden and Doughney 2009; Teachman 1987). For instance, Bowden and Doughney (2009) found that students from high-SES backgrounds have greater educational aspirations than their peers from low-SES backgrounds.

Summing these together, the research on SES have provided an insight into inequality associated with educational outcomes.

Questionnaires have typically been used to obtain data on students' socio-economic backgrounds and majority of SES measures is known to be obtained through interviews or surveys with parents (Ensminger and Fothergill 2003). Other less frequent sources of SES information is self-report from the youth (Ensminger and Fothergill 2003). The three variables normally asked about and used for measuring student/family SES in educational research (either as single indicators or in combinations) are as follows: (1) parental education, (2) parental occupation and (3) household resources or possessions (Schulz 2005).

Investigating the ways that SES is utilized and measured in research over a ten year period in North American Journals on children and adolescents, Ensminger and Fothergill (2003) found that overall, education was the most common indicator of SES, it was used 45% of 359 articles with SES included. Income was used in 28% of the articles, occupation was used in 14% of the articles, and participation in various means tested programs was used in 12% of the articles. Home resources or possession was not as a measure. However, home possession data collected from young children have been found to be much more reliable compared to information children provide about their parents' education, jobs, and income (Buchmann 2002; Keeves and Saha 1997; Postlethwaite 1999; Yang and Gustafsson 2004). For instance as Buchmann (2002, pp. 181–182) argues:

> *[A] careful assessment of the reliability and validity of home possessions as a measure of SES within countries and as a construct that holds cross-nationally may determine that home possessions data can provide better and more comparable measures of socioeconomic status than parental education and occupation.*

Moreover, using PIRLS 2006 data, Caro and Cortés (2012) found that parental occupational status was a better indicator of SES in the wealthier societies, whereas home possessions was a stable and reliable measure of SES in poorer societies. Irrespective of home possession, "home possessions play a less important role in measuring SES for wealthier societies" (Caro and Cortés 2012, p. 26).

In this study, we used data on home amenities to profile students' SES. We chose this approach because in addition to the above reasoning, student response when reporting parental education and occupation in educational research has been associated with high levels of non-response patterns and also a lack of comparability across countries (Schulz 2005). For instance, in TIMSS 2011 high percentage of Ghanaian students were unaware of their parents' education (IEA 2012). Moreover, home possessions indicate a family's lifestyle and socio-economic well-being, and more often than not are not influenced by a sudden change in income, education, or occupation (Yang and Gustafsson 2004). Furthermore, home support and demographic variables have been found to significantly reduce the effect of poverty on literacy development and children's academic growth (Entwistle et al. 1997; Lee and Croninger 1994).

The present study

The purpose of this study is to profile students' SES on the basis of their reported home resources, based on the TIMSS 2011 study. The following hypotheses guide the study: more than one student SES profile exists, and membership in the different profile groups is associated with several demographic home resources. The study also assumes that if we want to compare the distribution of educational achievement across/within society, a sound measurement of the SES of a person, group, or geographical region is important so as to capture and understand changes to the structure of a society, to understand the level of stratification or inequality in or between societies, and to understand the intergenerational change of social status over time (Oakes n.d.; Oakes and Rossi 2003; Wong 1998).

This paper extends the literature on SES because indigenous research and theorizing are integral part of establishing a more useful and universal theories. Moreover, cultural differences in SES can challenge the foundations of current theories and provide new ways of looking at the relationship between SES and educational outcomes. This paper uses TIMSS 2011 data, which is a more representative sample of developing country under study.

However, a deeper understanding of the complex interplay between home resources/possesses is paramount for helping society formulate policies that will assist children from disadvantaged home in particular. Moreover, there is a paucity of SES studies in the Ghanaian context.

Design

Participants

The study focuses on Ghanaian eighth graders who participated in the TIMSS 2011. The sample consists of 7323 students (47% girls, average age of 15.81) involving 161 schools/classrooms. Participation coverage was 100 percent, with school-level exclusions consisting of special education schools and small schools with fewer than 10 students (Martin and Mullis 2012).

Weighting and clustering

The analysis was based on TIMSS TOTWGT, which ensures that the weighted sample corresponds to the actual sample size. Another reason for using the sampling weights was to avoid bias (Bosker and Snijders 2011). Because class was used to uniquely identify the sampled classrooms in the data, it was used as the clustering variable.

Measures

The SES measures involve survey questionnaire concerning 11 household resources from the TIMSS 2011 (Table 1). The 11 items were used in the LCA, and were selected on the basis of responses from students on a number of general household items. The question was "Do you have any of these things at your home?" The items are shown in Table 1. Items 1–5 were common to all participating countries but items 6–11 were specific to Ghanaian students.

Table 1 Variables used in the study

	Yes	No
A: Socio-economic measure		
Do you have any of these things at your home?	1	2
(1) Computer	1	2
(2) Study desk/table for your use	1	2
(3) Books of your very own (do not count your school books)	1	2
(4) Your own room	1	2
(5) Internet connection	1	2
(6) Calculator	1	2
(7) Dictionary	1	2
(8) Electricity	1	2
(9) Car/motorbike/bicycle	1	2
(10) Tap water	1	2
(11) Chalk/blackboard	1	2
B: Gender		
1. Female 2. male		

Data analysis strategy

The analysis proceeded as follows. First, LCA was used to classify students into groups based on their reported 11 home resources (see Table 1: socioeconomic measures). We used a discriminant analysis to verify the degree to which groups were accurately classified (Hair et al. 2010). Measurement invariance of item thresholds and class probabilities across gender were evaluated. We used IBM SPSS version 22 (IBM Corp 2013) for the discriminate analysis. For other analysis, we used the statistical package *Mplus*, Version 7.2 (Muthén and Muthén 1998–2012).

For the LCA, the analysis was based on the *Mplus* robust maximum likelihood estimator (MLR) with robust standard errors. *Mplus complex mixture* data analysis was employed to account for the clustering (hierarchical structure) of the data. For the LCA, 2000 random sets of start values and 100 initial stage iterations were used, to address any problem of local maxima, (Geiser 2013; Muthén and Muthén 1998–2012; Uebersax 2000). In the LCA process, missing data were treated using the *Mplus* feature of full information maximum likelihood (FIML) (Asparouhov and Muthén 2010; Rubin 1987; Schafer and Graham 2002; Schafer 2010).

Once the best LCA model was obtained, we then tested for the gender invariance of class proportions and probabilities. An acceptable invariance model meant that male and female students have been sampled from the same population, have similar class proportions and conditional probabilities, and have responded similarly to the items.

Discriminant function analysis was used to determine which variables discriminated between the groups and how accurately individuals were classified into groups on the basis of selected variables (Tabachnick and Fidell 2001). Thus, the purpose of the discriminant function analysis was to evaluate the validity of the SES groups.

Classifying students into socio-economic profiles and goodness of fit

The first step in an LCA is to determine the number of groups, which should be well defined by well-differentiated profiles (Marsh et al. 2009; Pastor et al. 2007). In LCA research, the literature advises against using goodness-of-fit as a "golden rule" in identifying the number of latent class (Markland 2007; Marsh et al. 2004, 2009). Opinions differ on best to arrive at the appropriate number of groups in LCA analysis. Consistent with the LCA norm, in this study, solutions with varying numbers of classes/groups were estimated, and the one that make sense in relation to substantive theory, common sense, the nature of the groups, and group interpretability was used (Collins and Lanza 2010). In addition, the goodness-of-fit indexes and tests of statistical significance were taken into account (Collins and Lanza 2010; Marsh et al. 2009).

To compare the models' fit with the different number of classes; a Vuong–Lo–Mendell–Rubin (VLMR) (VLMR: Lo et al. 2001) test in addition to Bayesian information criterion (BIC) and sample-size-adjusted BIC (SSA-BIC) were used. These have been shown to help identify the correct number of latent profiles/classes (Nylund et al. 2007; Tofighi and Enders 2008). The VLMR test is based on the same principle as the LR difference test. The significant values of the VLMR test show that the estimated model fits significantly better than the model with one class less (Nylund et al. 2007).

Moreover, the latent class probabilities (Table 3), which indicates how individuals are assigned to their respective classes, were used for the class profiling. Furthermore, the average latent class assignment probabilities were accessed with values on the main diagonal being equal to or greater than 0.80 (Geiser 2013). As a guideline, the size of the smallest group of an acceptable solution should at least exceed 5% of the sample (Chow et al. 2012; Marsh et al. 2009). Table 2 lists the fit information for the models with one through five groups/classes. The BIC and the SSA-BIC indexes continue to decrease across the range of models considered, suggesting no specific number of groups. This may be due to the large sample size, as BIC is sample size dependent (Marsh et al. 2009). The VLMR results were inconsistent, being highly significant (p < .001) for the two-class solution but only marginally significant (p < .05) for the three-class solution. The VLMR results for the three-class solution were the best because the four-class solution was not as interpretable as the three-class solution. Average latent class probabilities for the most likely latent class membership were above the accepted cut-off mark (>0.70).

Moreover, an inspection of the log likelihood values indicated a sharp decrease from the 2-class solution to the 3-class and a very smooth decrease thereafter. The four-class solution contained a boundary estimate (two response probabilities were estimated to be exactly 0). The three-class solution had the highest entropy estimate (0.633 vs. 0.569 for the 3- and 4-class models, respectively), suggesting greater classification uncertainty with the extraction of one additional class. In addition, the log likelihood increased smoothly to reach a stable maximum in the 3-class solution compared to the 4-class model. The three-class solution was identified as the most optimal, because it appeared to provide a more reasonable representation of the data. The three-class solution was easy to interpret (and more parsimonious), and was further confirmed by the unique characteristics across the groups of the three-class model. Table 3 shows the latent class probabilities and Fig. 1 the estimated probability plots for both responses. The group membership information on each student was saved and used for further statistical analysis.

Results

The latent class analysis

Table 3 contains the response probabilities—the probability of being in a particular latent class and responding yes or no to the 11 latent class indicators obtained in the 3-class model. The first column (class 1) shows approximately 24% of the sample having a high item response. The students in this class have higher probabilities endorsement

Table 2 Indices for the latent class analysis

Class	p	log likelihood (L)	BIC	SSA-BIC	Entropy	VLMR	Average latent class probabilities		
							1	2	3
1	11	−47,836.032	95,769.878	95,734.922			0.850	0.003	0.147
2	23	−44,162.136	88,528.793	88,455.704	0.710	0.000	0.002	0.862	0.135
3	35	−43,715.660	87,742.546	87,631.324	0.633	0.035	0.104	0.104	0.793
4	47	−43,584.907	87,587.747	87,438.391	0.569	0.460			
5	59	−43,470.071	87,464.782	87,277.293	0.614	0.414			

BIC Bayesian information criterion, *SSA-BIC* sample-size-adjusted Bayesian information criterion, *VLMR* Vuong–Lo–Mendell–Rubin, *p* Number of parameter estimates

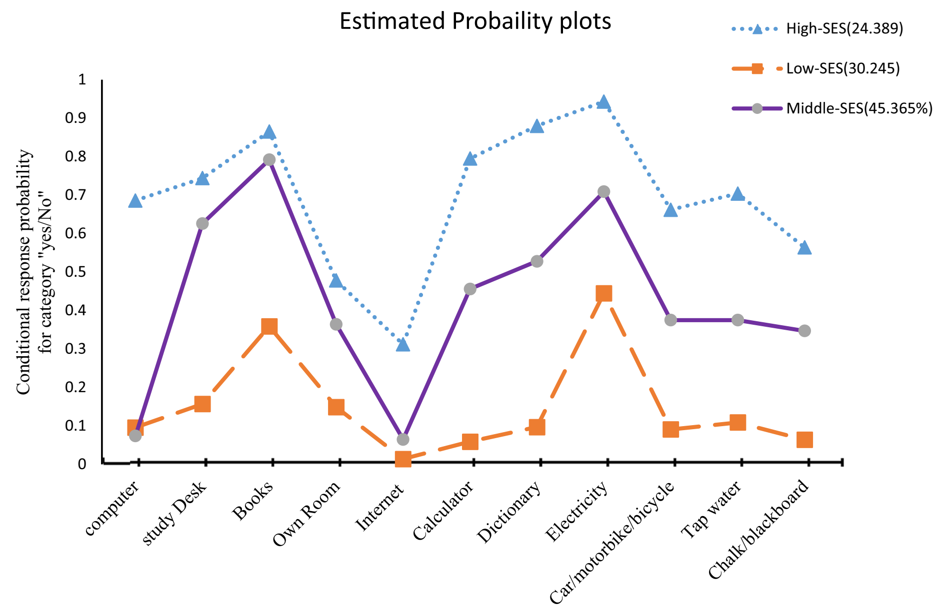

Fig. 1 Estimated probability plots indicating the socio-economic profiles of the students

for all items (electricity [0.943], dictionary [0.880], books [0.865], calculator [0.795], tap water [0.704], study desk [0.744], computer [0.686], car/motorbike/bicycle[0.662], chalk/blackboard [0.640] own room [0.478], internet [0.314],). For "own room" and "internet" the probabilities were lower than expected but not surprising for the sample per say. Yet, this class still had the highest probability endorsement. Due to this class's unique characteristics, it was named the 'high-SES'.

In the second column (class 2) approximately 45% (4-items) have a high probabilities endorsement (i.e. books [0.792], electricity [0.709], study desk [0.626], dictionary [0.528], and calculators [0.456]). Other items had a moderate endorsement probability except having a computer and internet access. Given this modest endorsement, the class was named 'middle-SES'. In the third column (class 3), approximately 30% of the sample fell within this category and had very low item response endorsement probabilities. The two highest probabilities across this class were electricity [0.445] and books [0.359]. Due to the pattern of endorsement, the class showed a pattern of students with a very low-SES, and was thus named 'low-SES'. Most students fell within the middle-SES class, followed by low-SES and high-SES. The class profile plot (Fig. 1) shows how the classes differ from one another.

Discriminant analysis

The LCA was followed by a discriminant analysis, used to determine which variables discriminated between the groups and to verify the degree to which groups were accurately classified. The discriminant analysis revealed two discriminant functions. Because there were three groups, only two discriminant functions were possible. The discriminant analysis based on the eleven household items was able to correctly classify 92.2% of the individual students into their appropriate SES group (based on the three LCA groupings). The two discriminant functions were statistically significant. However, the

Table 3 Latent class probabilities for the three SES classes

Items	Class 1 High-SES 24.3%	Class 2 Middle-SES 45.4%	Class 3 Low-SES 30.3%
Computer			
Yes	0.686	0.074	0.096
No	0.314	0.926	0.904
Study desk			
Yes	0.744	0.626	0.157
No	0.256	0.374	0.843
Books			
Yes	0.865	0.792	0.359
No	0.135	0.208	0.641
Own room			
Yes	0.478	0.364	0.149
No	0.522	0.636	0.851
Internet			
Yes	0.312	0.065	0.014
No	0.688	0.935	0.986
Calculator			
Yes	0.795	0.456	0.059
No	0.205	0.544	0.941
Dictionary			
Yes	0.880	0.528	0.097
No	0.120	0.472	0.903
Electricity			
Yes	0.943	0.709	0.445
No	0.057	0.291	0.555
Car/motor/bicycle			
Yes	0.662	0.375	0.091
No	0.338	0.625	0.909
Tap water			
Yes	0.704	0.375	0.109
No	0.296	0.625	0.891
Chalkboard			
Yes	0.564	0.347	0.064
No	0.436	0.653	0.936

first one account for 89.73% of the between-group (explained) variance while the second accounts for the remaining between-group variance (i.e., 10.27%). The squared canonical correlations, and the effect sizes for the discriminant functions, were 0.823 and 0.347, respectively.

The stability of the classification procedure was checked by a cross-validation run. Approximately 25% of the cases were withheld from the calculation of the classification function in this run. For 75% of the cases from which the functions were derived there was a 92.2% correct classification rate. For the cross-validation cases, correct classification was 92.1%. This indicates a high degree of consistency in the classification scheme. The discriminant function plot (Fig. 2) shows that the first function differentiated students in the high-SES from those in the low-SES group, and the second function differentiated the middle-SES group from the two other groups. In other words, it took both

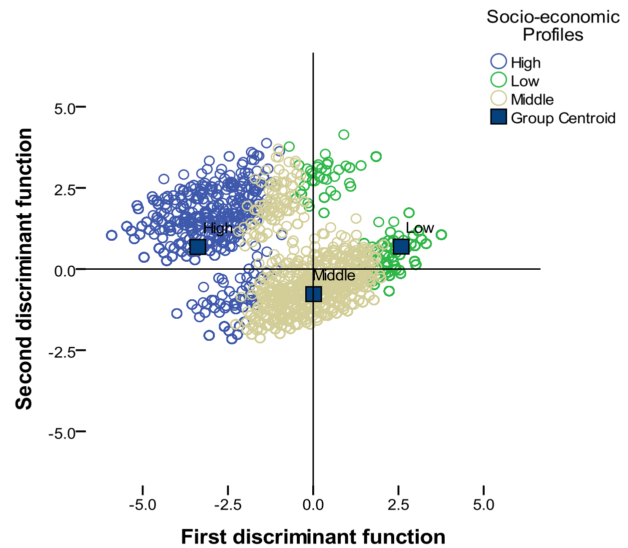

Fig. 2 Centroids of the three socio-economic profiles on the two discriminant functions derived from the data set

discriminant functions to separate the three groups from each other. This finding supports the validity of the three groups derived from the LCA. Most of the variance could be explained in terms of two discriminant functions.

Test of invariance across students' gender

The gender invariance of the class probabilities was tested to ascertain if the class probabilities (Table 3) were the same across students' gender and to help generalize the findings. Two models were tested, one freely estimating item thresholds and class probabilities across students' gender (M1) and another freely estimating item thresholds across the groups, fixing class probabilities and classes across the groups (M2) to be invariant. The entropy (M1 vs. M2: 0.793 vs. 0.791), BIC (M1 vs. M2: 97,865.560 vs. 97,864.250), and L^2 (M1 vs. M2: −48,617.107: scaling correction factor 2.971 vs. −48,625.344: scaling correction factor 2.870) were much the same.

The difference between the unconstrained (M1) and constrained model (M2) was not significant, ΔL^2 (2) $= 2.553$, $p = .279$, suggesting the constraints did not significantly affect the model fit. The two models were therefore not significantly different. The models indicated that the three SES classes were the same across students' gender. We can then generalize that in Ghana students socio-economic background can be categorized into low, middle and high, based on students' home resources.

Discussion

The reality of profiling SES is a complex enterprise far beyond TIMSS and other large scale studies. Using TIMSS 2011, we first use LCA to profile students into various SES based on their reported home resources. We then used discriminant analysis to verify the degree to which these groups are accurately classified and gender invariance was used to test if the class probabilities were the same across gender. It can be concluded from the results of the present research, that students' reported household resources provide comprehensive data on family background. We think the approach considered here will serve as a practical guide for educational researchers seeking to construct a reliable SES measure in low-income societies and in studying educational inequalities related to family background when using large scale international studies.

The analysis identified three classes of students based on reported home resources namely: high-SES, middle-SES, and low-SES. These classifications accord with the literature (e.g., Sirin 2005). The discriminant analysis was able to correctly classify 92.20% of the individual students into their appropriate SES group. A cross-validation run was carried out and the classification was 92.10%, which indicating a high degree of consistency in the classification scheme.

High-SES students' were those with access to all the listed home amenities. The items that differentiated students from the high- and middle-SES backgrounds were access to computers and the internet, and having electricity at home. Those in the low-SES class were students with a high probability having none or very limited access to the listed household items. Students' from low-SES homes lacked basic access to educational materials (e.g. books). This finding is in line with the literature in that low-SES families have limited financial resources, which restricts their ability to provide their children with learning materials (e.g., Orr 2003). We need to recognize that access to these amenities is an element of students' SES, which is also affected by parents' financial resources.

The most significant limitation of the study is that all measures are self-reports and thus subject to desirability biases. Another limitation is that in developing countries such as Ghana, goods are frequently purchased through nonmonetary systems, which makes it difficult to validate respondents' claims about home possessions. However, the meaning of home possessions differs across cultures even within a country. Moreover, the home resources used as a measure of SES were in this study not exhaustive enough, although the resources listed were sufficiently broad to allow for a differentiation of living standards across all households. For example, items such as tablets should be included in the next round of the survey. One practical problem, however, is the current lack of standardization across countries with respect to the core group of household items in the TIMSS data set. For instance, in the TIMSS 2011, six of the 11 home resources were country-specific whereas five were common to all participating countries. However, in most cultural settings different meaning are attached to these common household items. To adopt the SES approach universally, large scale international studies and survey developers should consider defining a set of socioeconomic variables that can be collected evenly across countries. The strength of the study is that the data set is a country representation and the robust methodology allows for a generalization of the results to Ghanaian grade eight students.

This study serves as a practical reference for education researchers and policy-makers in their efforts to better understand the SES composition in Ghana and to provide equal educational opportunities for all. Organizations may also use the findings of the study as a tool for understanding student composition in order to form better educational policy. For instance, to help improve schools in low-SES vicinities, governments and policy-makers should focus on teaching and learning, creating a positive school culture, and seeking external support and resources (Muijs et al. 2005).

In accordance with awareness of the educational and achievement disparities between different SES groups, the present findings can help educators and policy-makers make informed decisions and provide the right incentives to under privileged families. The findings can also help researchers explore other factors that might have an influence on students' SES. Most importantly, the study makes an important contribution to the field, because where reliable measures of SES are not available; as the case of our present data set (e.g., parental education and parental occupation), home resources are the most practical alternative. Moreover, the variables chosen embody strong theoretical consideration (Filmer and Pritchett 1999; Schulz 2005), and a most robust method was used to explore these findings.

Authors' contributions

EAB drafted the manuscript. MSH was EAB doctoral supervisor and shared his expertise during the preparation and the development of the manuscript. The work as a whole is an extensive collaboration and discussion between EAB and MSH. Both authors read and approved the final manuscript.

Authors' information

Emmanuel Adu-tutu Bofah had his Ph.D. at University of Helsinki, Finland, under the supervision of Professor Markku S. Hannula. He obtained his MA (Educational Science) and MSc (Social Science) from the University of Turku, and Helsinki respectively, Finland. His research interest is mathematics affect and its relationships to students' achievement. He has also written methodology papers on cross-cultural research on affect. With Markku S. Hannula, he has published on methodological aspects of cross-cultural studies for both Sage and Springer. Markku S. Hannula is a professor of mathematics education and the Director of the Research Centre for Mathematics and Science Education (RCMSE) in the Department of Teacher Education at the University of Helsinki. His main research interests are the affective domain and problem solving in mathematics and he uses both qualitative and quantitative methods. He serves currently as a board member for the European Society for Research in Mathematics Education.

Competing interests

The authors declare that they have no competing interests.

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