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THE GENERATIVE MECHANISM OF SECONDARY SCHOOL STUDENTS' OCCUPATIONAL EXPECTATIONS IN THE BALTIC COUNTRIES: INFLUENCE OF FAMILY, SCHOOL, AND INDIVIDUAL SCIENCE LEARNING ACHIEVEMENT

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Abstract. *Gender, learning achievements, parents' occupational status, social-economic backgrounds, and a few traits of schools affect students' occupational expectations. However, no research had integrated the above factors to investigate the generative mechanism of students' occupational expectations. After combining student-level and school-level PISA 2018 datasets, two-level latent covariate modeling was used to find the generative mechanism of students' occupational expectations in the Baltic countries. The mechanism had its primary concern to understand roles parents' occupational status and individual science learning achievement played on students' occupational expectations. The results indicate that the generative mechanism of students' occupational expectations of Lithuania, Estonia, and Latvia are the power model, the maternal model, and the science learning achievement pattern, respectively. It suggests one parent having high occupational status is to mold children's high-skilled occupational expectations, and it would be better the mother is the higher occupational status parent. It highlights the importance of strengthening adult education, especially that aimed at families with both parents of low occupational status. It disapproves of a mother being a full-time housewife. It may impede her children from having ambitions for high-skilled jobs.*

Keywords: *occupational expectation, PISA 2018 datasets, science learning achievement, two-level latent covariate model*

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Introduction

The BBC documentary series, "7 UP" shows even the preschool children having occupational aspirations to be the horse trainer, the scientist, so they can earn some money to make a living in the future. Some of them were well aware of the educational trajectory for which primary school and which university they should attend to achieve their aspirations. For some of them, the occupational aspirations eventually came to be their employment status as they accomplished the pre-designed educational trajectory. For the others, they got hired based on the achieved educational outcomes. The longitudinal interviews conducted in "7 UP" showed the schooling, the family, and persons themselves playing big roles in their occupational aspirations and the achieved occupational status. Scholars used to ask youngsters questions like "what kind of job would you like to do?" (Beal & Crockett, 2010; OECD, 2019). Answers to this kind of question are coded as occupational aspirations. Students' replies on "what work do you think you will probably do when you are about 30 or 35 years old" are coded as occupational expectations (Beal & Crockett, 2010; Hardie, 2015; OECD, 2019). Compared with occupational expectations, occupational aspirations relating to youngsters' occupational preferences are much less realistic (Beal & Crockett, 2010; Gottfredson, 1981; Wicht & Ludwig-Mayerhofer, 2014). Career choice or perceived occupational efficacy (Bandura, 1986) is a similar concept relating to occupational aspirations and occupational expectations (Rowan-Kenyon et al., 2011). Owing to Bandura et al. (2011) defined it as an occupation that students would consider choosing for their lifework, it more inclines to the connotation of occupational expectations. Occupational status is more realistic than the previous three concepts as it refers to young people's employment status when they left schools (Manzoni, 2018; Yates, 2011). In order to avoid unemployed, uneducated, or untrained in their adult lives (NEET; Yates, 2011), students need to

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be aware of their occupational expectations, make efforts to achieve corresponding educational outcomes, and getting hired by their professional skills. That is of great significance for themselves, their families, and society.

Literature Review

Compared with the 20th century, the developed Internet and the emergent general artificial intelligence in the 21st century remold the labor market and youngsters' career choices. To prepare students well for the changing surroundings highlights the need for understanding the generative mechanism of their career choices. Various conceptual frameworks, such as the pipe theory (Blickenstaff, 2005), the social cognitive theory (Bandura et al., 2011), and the social cognitive career theory (SCCT; Lent et al., 1994) were used by scholars to investigate the influential factors or mechanisms of youngsters' career choices. On the whole, these frameworks claimed four dimensions of influential factors. They are the social environment, the individual, the family, and the school system.

Gender, race, and expected financial gains are social environment determinants of teenager career choices. In the 1970s, many US minorities and girls were not active in pursuing high-skilled careers (Ginzberg, 1972). Research of the past three decades showed both the stubbornness and changes of these stereotypes. Bigler et al. (2003) found that though African American children rated occupations dominated by European Americans higher status than that dominated by African Americans, they thought they could pursue careers that used to be dominated by European Americans. By analyzing the Dutch survey data, Korupp et al. (2002a) declared that mothers' female sex-typed occupational status led to daughters' low career status. However, by analyzing the California survey data, Feliciano and Rumbaut (2005) observed the increasing trend of young women earned jobs previously male-dominated. In the global view, based on the dataset of the PISA 2000 test that has approximately 170,000 participants, Marks (2010) pointed out the facts that girls had higher occupational expectations than boys. After analyzing the PISA 2006 survey data, Sikora and Saha (2009) exposed that girls were more apt to have professional jobs than boys. They claimed that the stereotype that girls are more favorite to caring occupations, boys are more inclined to enterprising occupations is not that strong as before. In addition to race and gender, physical outcome expectations (financial gains) identified by Bandura (1986) influence youngsters' career choices. Shoffner et al. (2015) employed focus group interviews with 95 US students aged 10-14 to confirm that physical outcome expectations can motivate these preadolescents' career choices. The interviews and questionnaire survey to Serbia secondary school students again confirms physical (profitable) outcome expectations are major reasons for students' career choices (Maksimović et al., 2020).

Learning experiences, learning outcomes, and self-evaluative outcomes are the individual determinants of student career choices. Social learning theory (Krumboltz, 1994) and social cognitive career theory (Lent et al., 1994, 2000) raise that learning experiences can affect student career choices. Wild (2015) provided direct evidence that constructivist learning experiences are enhancing students' science-related career choices. The pipeline metaphor supports these two theories by claiming that college students who major in STEM must have learned calculus in their high school period (Adelman, 2006). However, Cannady et al. (2014) questioned it as they found that 48% of scientists or engineers did not have a learning experience of calculus in high schools. There are two kinds of learning outcomes, learning achievements and educational attainments. Students' learning achievements are periodic fruits of their schooling, whereas educational attainment is academic certificates students attain when they leave schools. The better students' learning achievements in reading, mathematics, and science, the higher occupational expectations they hold (Marks, 2010; Wicht & Ludwig-Mayerhofer, 2014). Based on datasets from the United States National Education Longitudinal Study of 1988, Tai et al. (2006) argued that students' eighth-grade mathematics achievements significantly result in students' majoring and earning physical science and engineering degrees. The connection between educational attainments and occupational status was found by Schoon and Parsons (2002). However, based on structural equation modeling using a dataset with 272 Italian children, Bandura et al. (2001) contended that student learning achievements had little influence on their career choices. It was the perceived self-efficacy on academics that had a significant effect on student career choices. Meanwhile, through hierarchical linear modeling on a sample of 23,100 respondents in 14 European countries, the strong relationship between educational attainments and occupational status is only found in strong vocational orientation countries (Andersen et al., 2010). Self-evaluative outcomes (Bandura, 1986) are another individual determinant of students' career choices. It includes intrinsic motivation (e.g., interest, needs, and attitudes) and external motivation (e.g., rewards). Among them, interest is frequently found to be an influential factor in students' career choices (Adelman, 2006; Dewitt et al., 2011; Gottfredson, 1981; Lent et al., 1994, 2000; Maksimović et al., 2020; Shoffner et al., 2015; Super, 1980).

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Parents' occupational status, parents' attitudes, and parents' socioeconomic status are family determinants of youngsters' career choices. Based on the General Social Survey data, Hout (2018) found that both fathers' and mothers' occupational status significantly affected US youngsters' occupational status. From a Japanese sample of 1621 individuals, Tsukahara (2007) found that a father's occupational status affected his children's career choices. As mentioned earlier, learning outcomes can be predictors of youngsters' career choices. Therefore, if parents' occupational status influences children's learning outcomes, it may affect children's career choices. Using cross-sectional data from the National Survey of Families and Households, Kalmijn (1994) argued that a mother's occupational status strongly affected her children's learning outcomes, and the influence of a father's occupational status on his children's learning outcomes was decreasing. Whereas Korupp et al. (2002b) contended that fathers' and mothers' occupational status affected their children's learning outcomes with an integrated dataset of the Netherlands, West Germany, and the US respondents. In sum, previous research suggested that parents' occupational status affected children's career choices/learning outcomes, whether it was a father's occupational status, a mother's occupational status, or both. As far as parents' attitudes are concerned, parents' attitudes toward science influence their children's occupational aspirations of science-related careers (Dewitt et al., 2011). Jodl et al. (2001) had done a questionnaire survey to 444 seventh-grade US students. They found that parents' assessment of their children's learning ability can predict their children's confidence and outcomes in school subjects, as well as career choices. The researchers find that parents' socioeconomic status significantly affects children's career choices. Children in advantaged socioeconomic backgrounds gain better occupational status or have higher occupational expectations than those in disadvantaged backgrounds (Croll, 2008; Mann et al., 2020; Marks, 2010). Schoon and Parsons (2002) argued that parents' socioeconomic status directly influenced children's occupational status, and indirectly influenced children's occupational status by two mediators of children's occupational aspirations and educational attainments. The more direct cash transfer from parents the US youngsters aged 18 through 28 received, the better their occupational status was if they use the money to pay for college fees or training fees to improve their educational attainments (Manzoni, 2018). However, Bandura et al. (2001) contended that parents' socioeconomic status had no direct impact on children's career choices but could influence children's career choices by mediators of parent's academic efficacy and parent's academic aspiration. In sum, socioeconomic status affects children's career choices, whether it plays as a direct effect or an indirect effect.

The school system affects youngsters' career choices. The highly stratified school system characterized by various school types, such as Hauptschule and Realschule, significantly influences youngsters' career choices (Wicht & Ludwig-Mayerhofer, 2014). Besides, Wicht (2016) had reported that schools enrolling immigrants could prompt both immigrants and native youths' occupational aspirations. Career guidance provided by schools is another influential factor in students' career choices. In schools which resources are scarce, though some students have ambitious career plans, the only available counselors are their teachers (Rowan-Kenyon et al., 2011). For schools where social-economic advantaged students are mass, students are more likely to receive professional career guidance (Mann et al., 2020). As educational attainments and occupational expectations were not always well aligned, Croll (2008) had argued that the teachers should pay more effort to guide students of high educational attainment and low occupational expectations in disadvantaged backgrounds. The higher these students' occupational expectations prompted, the better occupational status they achieved in adulthood. However, PISA 2018 results also indicated that career guidance did not result in students' high-skilled occupational expectations in some countries (OECD, 2020a).

Though much research has explored the mechanism accounting for the US, the UK, and German students' career choices, little research said about this mechanism for students in the Baltic countries. For school systems, the research about impacts of school types and career guidance on students' career choices was mass, but rarely in research on the influence of school size, class size, and student-teacher ratio on students' career choices. Studies in this field seldomly employed the PISA dataset, while the occupational expectations were core concerns of PISA tests. It collected information about various influential factors of students' career choices. Not much previous research reported its determination coefficients. However, in the case of the determination coefficient was small, it implied the regression coefficients of predictors on career choices were inaccurate. Besides, little research has reported whether or not there was a dominant factor among all these influential factors.

Research Focus

This research focused on the generative mechanism of secondary school students' occupational expectations of the Baltic countries. It is intricate as many factors affect students' occupational expectations. Therefore,

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this research raised its primary concern as understanding the impact of parents' occupational status on students' occupational expectations. The reason for it was the previous research had shown that parents' occupational status positively affected students' occupational expectations in most cases. Compared with parents' occupational status, other influential factors of students' occupational expectations demonstrate unstable or weak effects. For example, interests in a specific subject may or may not play significant roles in students' occupational expectations; girls may or may not have higher occupational expectations than boys. The relation of parents' occupational status and students' occupational expectations is the base, through including other key factors enable this research building the generative mechanism model of students' occupational expectations.

Korupp et al. (2002b) summarized five models that explained the influence of parents' occupational status on children's education. The predictive variable in the conventional model is father's occupational status; in the maternal model is mother's occupational status; in the power model is the highest occupational status; in the individual model is father's and mother's occupational status; in the joined model is the average of father's and mother's occupational status (Korupp et al., 2002b). By changing the outcome variable to be children's occupational expectations, models summarized by Korupp et al. (2002b) can be adopted as the baseline model of this research.

As there are different opinions on the role learning achievements playing in students' career choices, this research also intends to find whether students' ability in science impacts their career choices. In PISA 2018 tests, the international standard classification of occupations (ISCO) codes 2 to 3 was assigned to science-related careers, which are high-skilled occupations (OECD, 2019). In theory, students' science-related occupational expectations originate from their science learning achievements. Across OECD countries, for students who participated in the PISA 2018 tests, 76% of them held high-skilled occupation expectations. However, among these students, 20% had no intention of going to college (OECD, 2019). It was a sign that they may not be good at school subjects, and it did not impede them from pursuing high-skilled occupations.

Research Aim and Research Questions

This research aimed to put forward the generative mechanism of secondary school students' occupational expectations. The generative mechanism is something that explains the formation and changes of students' occupational expectations. Specifically, this mechanism is a model depicting how the socialization process to yield students' self-awareness on their roles in future labor markets is done. This model is structured with a set of factors in a certain way. Therefore, when changes in surroundings result in factors' variation, it would not be difficult to predict variations of students' occupational expectations according to the model.

The research questions were:

1. To what extent were students' occupational expectations the result of their parents' occupational status? For the conventional, maternal, power, individual, and joined model, which one was best fitting the PISA 2018 datasets of the Baltic countries?
2. Science-related careers are high-skilled occupations. In this context, were students' science learning achievements significant roles in forming their occupational expectations?
3. Were parents' occupational status the most important predictor of children's occupational expectations?

Research Methodology

General Background

PISA 2018 dataset is a free resource at the OECD's Programme for International Student Assessment website, and researchers are permitted to use this dataset to do their analysis (OECD, 2020b). The student-level (micro-level) dataset provides information about influential factors of students' occupational expectations in the dimensions of the social environment, the individual, and the family, such as gender, learning achievements in science, attitudes toward school and learning, parents' education, and parents' career status. The school-level (macro-level) dataset provides information about influential factors of students' occupational expectations in the school system dimension. Thus, the combination of student-level and school-level datasets provided this research the convenience of exploring the mechanism of students' occupational expectations production from a holistic viewpoint. Variables in the PISA dataset are categorized as questionnaire items and derived variables. The derived variables were constructed either by the arithmetical transformation of questionnaire items or by item response theory scaling

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procedures (OECD, 2020c). The research only took derived variables into model training because questionnaire items were trivial and too many. For condensing information, derived variables extracted the common traits from several questionnaire items (OECD, 2020c). Thus, the application of derived variables allowed researchers to do their analysis with fewer variables without losing the quality of information.

According to the research focus, research aim, and research questions, this research used two-level latent covariate modeling rather than single-level modeling as its statistical technique. As the relationship between antecedent variables and outcome variables may change in different levels, extending the results at student-level to school-level could lead to atomistic fallacy (Hox, 2010, p. 3). Therefore, it made sense to differentiate the generative mechanisms of students' occupational expectations at different levels. The advantages of two-level latent covariate modeling also stand in the following two aspects. First, as a manifest-latent model, the two-level latent covariate model has its superiority in correcting sampling error (Lüdtke et al., 2011). Second, in terms of measurement error, since derived variables were constructed by multiple items rather than an item, the measurement error had been corrected (Lüdtke et al., 2011). In sum, the two-level latent covariate modeling made the results of this research reliable.

Sample

There were 5316 Estonian secondary school students in 230 schools; 5303 Latvian secondary school students in 300 schools; 6885 Lithuanian secondary school students in 362 schools who completed PISA 2018 tests (OECD, 2020b). Since this research was interested in the fixed effects and variance components, the nested data structure required lots in the number of schools (Raudenbush & Liu, 2000). The rule of thumb for this situation is no less than 100 schools and no less than 10 students in the sampling size per school (Hox, 2010, p. 235; Silva et al., 2020, p. 38). Therefore, for these three samples, schools that had records smaller than 10 were deleted. The adopted Estonian dataset used in this research covered 172 schools and 5024 students. The Latvian dataset included 218 schools and 4662 students. The Lithuanian dataset included 256 schools and 6389 students.

Instrument and Procedures

There were 79 countries and economies that had completed student and school questionnaires (OECD, 2020c). According to tables 16.69, 16.108, and 16.113, the Baltic countries did not attend the parent, well-being, and teacher questionnaire surveys (OECD, n.d.). As table 16.83 shows, Lithuania participates in the educational career questionnaire survey (OECD, n.d.). Tables 16.71 and 16.89 show all three Baltic countries completing ICT familiarity and financial literacy questionnaire surveys (OECD, n.d.). Derived variables constructed from the educational career, ICT familiarity, and financial literacy questionnaire items were recorded in the student-level dataset (OECD, 2020b). Therefore, the combination of student-level and school-level datasets accumulated rich information about students' learning, parents' education, parents' occupational status, and schools' operation. That benefitted this research to construct the generative mechanism of students' occupational expectations using this comprehensive collection of factors.

Several derived variables were crucial for the interests of this research. The student's expected occupational status (BSMJ) was an outcome variable. Mother's occupational status (BMMJ1), father's occupational status (BFMJ2), and student's science learning achievement (PV1SCIE) were predictive variables (OECD, 2020b). The reason for incorporating other derived variables into model training was to achieve a better model fit and explanatory power. In this case, the partial regression coefficients of the predictive variables could be more reliable.

The research followed three steps to achieve its aims. Step 1: Exploring factors that had great explanatory power to BSMJ by simple linear regression method with the student-level dataset. Step 2: Computing the intraclass correlation (ICCs) of these significant predictive variables. ICC1>0.05 and ICC2>0.5 meant these variables were in accord with the marginal cutoff point for multi-level analysis (Cohen et al., 2003, p. 538; Dixon & Cunningham, 2006; Heck & Thomas, 2020, pp.34-37; Klein et al., 2000). Step 3: Applying two-level latent covariate modeling to discover the generative mechanism for secondary school students' occupational expectations through the combined dataset. R software was used in steps 1 and 2, and Mplus 7.4 software was used in step 3.

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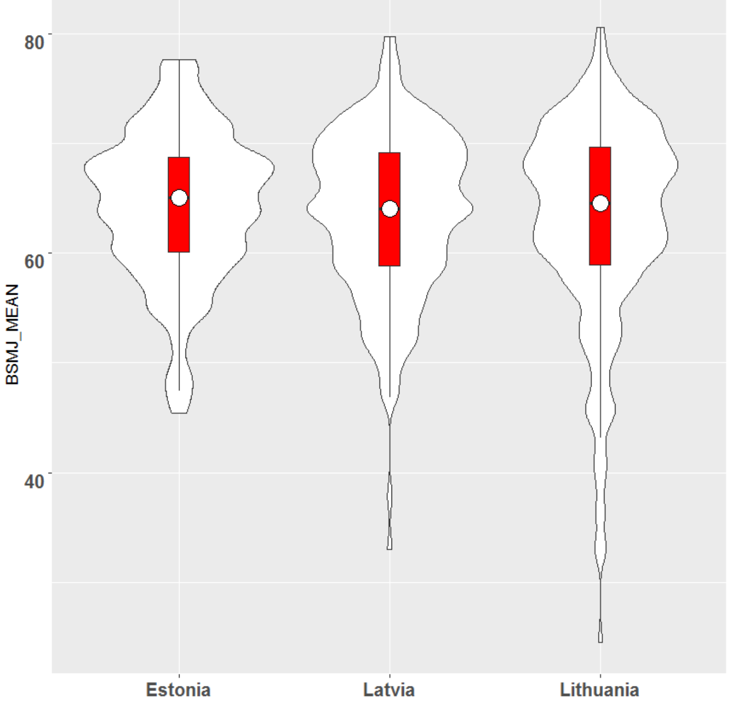
Data Analysis

The mean BSMJ value for each school in the Baltic countries was computed and visualized in figure 1. From the internal boxplots, most of the schools had a mean value of BSMJ above 60. Approximately 50% of schools in the 60~70 mean BSMJ value range. From the external kernel density plots, the Estonian sample was highest in the degree of data concentration. The rest samples were approximate in the degree of data concentration. For Estonian and Lithuanian samples, the schools whose mean BSMJ value was close to 70 were the most. For the Latvian sample, it had two frequency peaks near 65 and 70.

Figure 1
Violin Plot of the School's Mean Value of BSMJ of the Baltic Countries (Outliers Deleted)



Research questions 1 and 2 reflected the research focus. The equations for answering them were shown as follows:

Student-level equation:

$$Y_{ij} = \beta_{0j} + \beta_{1j} BMMJ1_{\_w} + \beta_{2j} BFMJ2_{\_w} + \beta_{3j} PV1SCIE_{\_w} + \beta_{4j} HYP\_A_w + \varepsilon_{ij}$$

School-level equation:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} BMMJ1_{\_b} + \gamma_{02} BFMJ2_{\_b} + \gamma_{03} PV1SCIE_{\_b} + \gamma_{04} HYP\_A_b + \gamma_{05} HYP\_B + \mu_{0j}$$

$$\beta_{1j} = \gamma_{10}; \beta_{2j} = \gamma_{20}; \beta_{3j} = \gamma_{30}; \beta_{4j} = \gamma_{40}$$

Mixed model equation:

$$Y_{ij} = \gamma_{00} + \gamma_{01} BMMJ1_{\_b} + \gamma_{02} BFMJ2_{\_b} + \gamma_{03} PV1SCIE_{\_b} + \gamma_{04} HYP\_A_b + \gamma_{05} HYP\_B$$
$$+ \gamma_{10} BMMJ1_{\_w} + \gamma_{20} BFMJ2_{\_w} + \gamma_{30} PV1SCIE_{\_w} + \gamma_{40} HYP\_A_w + \left(\mu_{0j} + \varepsilon_{ij}\right)$$

Y_{ij} was the BSMJ value of the *i*'th student in school *j*. $\varepsilon_{ij} \sim N(0, \sigma^2)$; $\mu_{0j} \sim (0, \tau_{00})$. In the mixed model equation, random effects were given in parentheses. The rest of the equation showed the fixed effects. Variable with the subscript w meant the within-group component of that variable, whereas variable with the subscript b meant the between-group component of that variable. HYP_A were the other derived variables in PISA 2018 student-level

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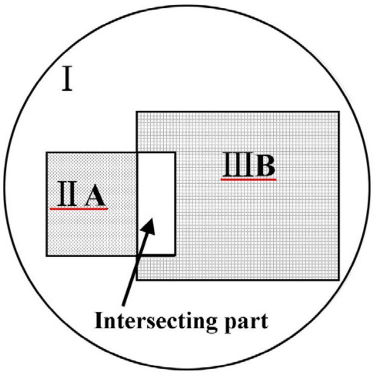
dataset that could enhance the explanatory power when adding them into the equation. HYP_B were school-level derived variables only used as school-level predictors, and the reason for including them in the equation was the same as HYP_A. Whether or not can BMMJ1, BFMJ2, PV1SCIE, and HYP_A decompose into components of within-group and between-group, depending on their estimated intraclass correlations. Therefore, the final accepted equations for Baltic secondary school students' occupational expectations may vary from this general equation.

For research question 3, the clue of analysis is according to figure 2. Circle I represents the total variance of BSMJ. Rectangles II and III represent the variance explained by predictive variables A and B, respectively. The intersecting part of II and III represents variance explained by variables A and B simultaneously. Therefore, comparing the explanatory power of variables A and B is equal to contrast the areas rectangle II and III subtracting the intersecting part. This kind of area represents the variance solely explained by a given variable.

Figure 2
Method Used to Compare the Explanatory Power of Different Predictive Variables



Research Results

Student-level Predictors of Students' BSMJ

All derived variables constructed by the student, ICT familiarity, financial literacy, and educational career (Lithuania only) questionnaire items (OECD, n.d.) were used as predictors for students' BSMJ in a simple linear regression method to examine their explanatory power. Table 1 shows the top seven powerful predictors for the three samples.

Table 1
Powerful Predictors of Students' BSMJ of the Baltic Countries

Lithuanian sample		Estonian sample		Latvian sample	
Predicator	R^2	Predicator	R^2	Predicator	R^2
PV1SCIE	.1471	PV1SCIE	.0778	PV1SCIE	.0928
ESCS	.0912	ESCS	.0508	ESCS	.0726
HISEI	.0766	HISEI	.0450	HISEI	.0657
HOMEPOS	.0568	MASTGOAL	.0430	BMMJ1	.0487
BMMJ1	.0553	ST004D01T	.0424	BFMJ2	.0399
BFMJ2	.0474	BMMJ1	.0349	HOMEPOS	.0347
CULTPOSS	.0449	BFMJ2	.0282	PAREDINT	.0311

Note. ESCS (index of economic, social and cultural status. It is a standardized value with an OECD mean of zero). HISEI (highest parental occupational status. It is the variable used in the power model). HOMEPOS (home possessions). CULTPOSS (cultural possessions at home). MASTGOAL (mastery goal orientation). ST004D01T (gender). PAREDINT (index highest parental education). ESCS was constructed by HISEI, HOMEPOS, and PAREDINT (OECD, 2020c).

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Table 1 shows PV1SCIE, ESCS, and HISEI are the top three powerful predictors of students' BSMJ of the Baltic countries. Learning achievements (PV1SCIE) was the strongest predictor found by the simple linear regression method. Predictor gender was found in the Estonian sample. The factor group in the family dimension (ESCS, HISEI, HOMEPOS, and PAREDINT) showed clearly in the Latvian sample. Since PV1SCIE, HISEI, BMMJ1, and BFMJ2 were powerful predictors in all samples, it strongly supported this study's research focus.

As BMMJ1 and BFMJ2 were used in constructing the individual model of students' BSMJ, whether there was a multicollinearity problem or not between them should be examined first. The variance inflation factor (VIF) for the Lithuanian sample was 1.1498; for the Estonian sample was 1.1199; for the Latvian sample was 1.1151. Since these VIF values were smaller than 10, there wasn't a multicollinearity problem between BMMJ1 and BFMJ2 (Darlington & Hayes, 2016, p.112). As ESCS and HISEI may co-exist in the power model of students' BSMJ, the multicollinearity examination it made for these two variables was also necessary. The VIF for the Lithuanian, Latvian, and Estonian samples was 3.8121, 3.1326, 3.6491, respectively. This kind of factor combination then does no damage to the power model. Nevertheless, combinations such as ESCS+HISEI+HOMEPOS, ESCS+HISEI+PAREDINT, ESCS+PAREDINT+HOMEPOS, and ESCS+HISEI+HOMEPOS+PAREDINT resulted in large VIF, thus should be excluded in modeling.

ICC1 and ICC2 account for the fitness of variables for multi-level analysis. Table 2 shows the ICC_s of both BSMJ and its powerful predictors.

Table 2
ICC_s of Both BSMJ and its Powerful Predicators

Lithuanian sample			Estonian sample			Latvian sample		
Variable	**ICC1**	**ICC2**	**Variable**	**ICC1**	**ICC2**	**Variable**	**ICC1**	**ICC2**
BSMJ	.1433	.7041	BSMJ	.0622	.6007	BSMJ	.0748	.5656
PV1SCIE	.3263	.9021	PV1SCIE	.2144	.8885	PV1SCIE	.1596	.8025
ESCS	.2378	.8522	ESCS	.1945	.8734	ESCS	.1645	.8047
HISEI	.1851	.7944	HISEI	.1618	.8388	HISEI	.1264	.7316
HOMEPOS	.1393	.7524	MASTGOAL	.1163	.7856	BMMJ1	.1112	.6771
BMMJ1	.1516	.7411	BMMJ1	.1439	.8075	BFMJ2	.1378	.7086
BFMJ2	.1681	.7511	BFMJ2	.1615	.8173	HOMEPOS	.0975	.6944
CULTPOSS	.1085	.6943				PAREDINT	.0975	.6921

Table 2 shows both BSMJ and its predictors meeting the requirements of multi-level analysis in all three samples. The heterogeneity that existed in schools could not be ignored.

The Generative Mechanism of Lithuanian Secondary School Students' Occupational Expectations

The student-level and school-level datasets were combined in this step. This data set gathered student-level derived variables shown in table 1 and derived variables constructed by the school questionnaire items. Since PV1SCIE and ESCS were the top two explanatory variables accounting for BSMJ's variance found by the simple linear regression method, three models (M_{00}~M_{02}) were constructed as baseline models first. M_{00} only decomposed the variable PV1SCIE into within-group and between-group parts based on the multi-level latent covariate method. The decomposition variable in M_{01} was ESCS. M_{02} decomposed PV1SCIE and ESCS simultaneously. The conventional, maternal, power, individual, and joined models were trained based on the baseline models. Table 3 shows the acceptable trained models and baseline models. The individual model could not be constructed.

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Table 3
Fixed Effects Estimates (Top), Random Effects Estimates (Middle), and Fit Indices (Bottom) for Models of the Predictors of Lithuanian Secondary School Students' Occupational Expectations

Parameter[a]	M_{00}	M_{01}	M_{02}	Model[b]			
				Conventi-onal	Maternal	Power	Joined
Fixed effect (unstandardized coefficient)							
Intercept (γ_{00})	3.88	42.85***	-46.71**	20.21***	19.20***	13.35**	18.97***
PV1SCIE_w	-.25***		-.06***				
ESCS_w		.58***	.55***	.42***	.45***	.39***	.42***
HISEI_w						.52***	
BMMJ1_w					.43***		
BFMJ2_w				.47***			
BMJOIN_w							.50***
PV1SCIE_b	.09**		.18***				
ESCS_b		.24***	.57***.	.37**	.40***	.37***	.37**
HISEI_b						.50***	
BMMJ1_b					.38***		
BFMJ2_b				.44***			
BMJOIN_b							.43***
STRATIO				-.14***	-.15***	-.13***	-.14***
SCHSIZE				.07***	.08***	.06***	.08***
Random effect (unstandardized coefficient)							
Intercept (τ_{00})	128.23**	132.12***	69.06**	2.64	3.15	1.82	2.80
Residual (σ^2)	4184.87***	2568.96***	2543.43***	2081.08***	2179.43***	1916.72***	2086.28***
Model fit[c]							
LL	-49074.39	-47424.21	-72325.51	-127503.60	-127555.82	-127461.71	-173063.16
AIC	98158.78	94858.42	144665.02	255025.37	255129.65	254941.41	346156.33
BIC	98190.55	94890.19	144709.49	255082.55	255186.83	254998.59	346251.63
R^2_within level	.11***	.45***	.457***	.55***	.53***	.59***	.55***
R^2_between level	.15	.11	.544***	.98***	.98***	.99***	.98***

Note. [a] PV1SCIE_w and PV1SCIE_b represent the within-group and between-group parts of PVISCIE, respectively. The same is true for the other predictors. BMJOIN = (BMMJ1+BFMJ2)/2. STRATIO (student-teacher ratio). SCHSIZE (the total enrolment at school). [b] The best fitting models were constructed based on M_{01}. [c] LL = log-likelihood, AIC = Akaike information criteria, BIC = Bayesian information criteria.

In terms of theory-driven, this research aimed to find the model having maximum explanatory power. In terms of data-driven, this research took testing of model fit seriously. If the model fitting is the only consideration, the social phenomenon would be a puppet of mathematics. If explanatory power is the only consideration, the conceptual framework could impede mathematics voicing. Therefore, the main idea here was to find an equilibrium point between explanatory power and fitting data.

The best-fitting model was M_{01}, which was maximum in log-likelihood and minimum in AIC and BIC. Nevertheless, M_{01} was weak in its explanatory power, depending on the ESCS_b only explains 11% BSMJ variance in school-level. The conventional, maternal, power, and joined models had good explanatory power. Compared with M_{01}, they had approximately 10% increases in within-level *R* square and 80% increases in between-level *R* square.

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An increase in *R* square should not lead to a significant increase in information criteria. The joined model was good at its explanatory power but worst in its model fit indices. It made the power model the best for explaining the generative mechanism of Lithuanian secondary school students' occupational expectations. Compared with the conventional, maternal, and joined models, the power model had the maximum log-likelihood and the minimum AIC and BIC.

The mixed model equation explaining Lithuanian students' occupational expectations was:

$$Y_{ij} = 13.35 + 0.50HISEI_{\_b} + 0.37ESCS_{\_b} - 0.13STRATIO + 0.06SCHSIZE + 0.52HISEI_{\_w} + 0.39ESCS_{\_w} + (1.82 + 1916.72)$$

At the student level, the higher individuals' HISEI and ESCS, the greater their BSMJ. At the school level, the higher a school's average students' HISEI and ESCS, the greater its students' average BSMJ. Increases in teacher numbers and student enrollment also contributed to increasing a school's students' average BSMJ.

For examining the explanatory power of HISEI to Lithuanian students' occupational expectations, a new model that excluded HISEI was constructed. Its parameter estimates are shown in table 4. Using the method introduced in figure 2, in contrast with the power model, it found HISEI contributing 14% explanatory power to the within-level variance of BSMJ and 2% explanatory power to the between-level variance of BSMJ. It made HISEI not a dominant predictor of students' BSMJ.

Table 4
Parameter Estimates of HISEI Excluded Model of Lithuanian Students' Occupational Expectations

Fixed effect[a]					Random effect[a]		*R* square	
Intercept (γ_{00})	ESCS_w	ESCS_b	STRATIO	SCHSIZE	Intercept (τ_{00})	Residual (σ^2)	Within level	Between level
32.55***	.58***	.57***	-.16***	.10***	5.06	2557.95***	.45***	.97***

Note. [a] unstandardized coefficient.

The Generative Mechanism of Estonian Secondary School Students' Occupational Expectations

Table 5 shows that M_{00}~M_{02} fail in the Estonian sample. For M_{00}, the unstandardized coefficient of PV1SCIE_b was insignificant; the unstandardized coefficient of PV1SCIE_w was significant but negative. It violated the finding PV1SCIE was a positive predictor of students' BSMJ in a simple linear regression method. This kind of situation also appeared in M_{01} and M_{02}. Once again, the individual model was not available; the joined model was not good at its fit indices. For the rest three models, though the maternal model did not have the maximal explanatory power to the between-level variance of BSMJ, it best fitted the data. So, it represented the generative mechanism of Estonian secondary school students' occupational expectations.

Table 5
Fixed Effects Estimates (Top), Random Effects Estimates (Middle) and Fit Indices (Bottom) for Models of the Predictors of Estonian Secondary School Students' Occupational Expectations

Parameter[a]	M_{00}	M_{01}	M_{02}	Model			
				Conventi-onal	Maternal	Power	Joined
			Fixed effect (unstandardized coefficient)				
Intercept (γ_{00})	94.15**	106.24***	153.71	76.97***	78.37***	41.77**	78.04***
PV1SCIE_w	-.22***		-.22***				
ESCS_w		.07	.01				

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Parameter[a]	M_{00}	M_{01}	M_{02}	Model			
				Conventi-onal	Maternal	Power	Joined
HISEI_w						.49***	
BMMJ1_w					.68***		
BFMJ2_w				.55***			
BMJOIN_w							.69***
PV1SCIE_b	.02		-.09				
ESCS_b		-1.927	-2.77.				
HISEI_b						1.09***	
BMMJ1_b					.85***		
BFMJ2_b				.92***			
BMJOIN_b							.89***
STAFFSHORT				-.12***	-.12***	-.07*	-.12***
Random effect (unstandardized coefficient)							
Intercept (τ_{00})	759.54**	724.87***	715.30***	90.51	136.38	60.18	99.51
Residual (σ^2)	9850.35***	10499.17***	9849.89***	8880.33***	8463.23***	9044.60***	8440.20***
Model fit							
LL	-40834.74	-36354.06	-56906.14	-65662.04	-65313.27	-65898.62	-103241.57
AIC	81679.43	72718.12	113826.28	131336.09	130638.54	131809.24	206507.15
BIC	81710.04	72748.68	113869.07	131372.77	130675.22	131845.92	206580.51
R^2_within level	.06***	.00	.06***	.16***	.20***	.14***	.20***
R^2_between level	.00	.04	.06	.88***	.82***	.92***	.86***

Note. [a] STAFFSHORT (shortage of education staff).

Only one HYP_B factor, STAFFSHORT, could be incorporated into the acceptable trained model. The mixed model equation explaining Estonian students' occupational expectations was:

$$Y_{ij} = 78.37 + 0.85BMMJ1\_{b} - 0.12STAFFSHORT + 0.68BMMJ1\_{w} + (136.38 + 8463.23)$$

Shortage of education staff had a negative influence on average students' BSMJ of a school. BMMJ1_w was the dominant predictor of BSMJ at the student level as it was the only factor incorporated in the student-level equation and accounted for 20% within-level variance of BSMJ. To compare the explanatory power of BMMJ1_b and STAFFSHORT, a new model that excluded BMMJ1 was constructed. Its parameter estimates are shown in table 6.

Table 6
Parameter Estimates of BMMJ1 Excluded Model of Estonian Students' Occupational Expectations

Fixed effect[a]		Random effect[a]		*R* square	
Intercept (γ_{00})	STAFFSHORT	Intercept (τ_{00})	Residual (σ2)	Within-level	Between- level
134.68***	-.14***	487.28	10505.27***	0	.35***

Note. [a] unstandardized coefficient.

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BMMJ1_b explained 47% between-level variance of BSMJ, which was not related to STAFFSHORT. Though STAFFSHORT explained 35% between-level variance of BSMJ, some of this explanatory power was shared by BMMJ1_b. Taking the maternal model as a baseline model, STAFFSHORT excluded resulted in 59% between-level variance of BSMJ explained by BMMJ1_b. Therefore, BMMJ1_b and STAFFSHORT shared the 12% explanatory power. STAFFSHORT explained 23% between-level variance of BSMJ independently that was not related to BMMJ1_b. In sum, BMMJ1_b was the dominant predictor of the between-level variance of BSMJ.

The Generative Mechanism of Latvian Secondary School Students' Occupational Expectations

Table 7 shows that the maternal model is the only available model for the Latvian sample except for the baseline models. The maternal model did not include the between-level component of BMMJ1. If BMMJ1_b entered, the unstandardized coefficients of BMMJ1_w and BMMJ1_b would turn into insignificance. That was contrary to BMMJ1 as a significant predictor of BSMJ shown in table 1. For models shown in table 7, M_{00} is best accounting for the generative mechanism of Latvian students' BSMJ. M_{00}, M_{02}, and the maternal model had roughly the same explanatory power to students' BSMJ, whereas M_{00} had the maximum log-likelihood and the minimum AIC and BIC.

Table 7
Fixed Effects Estimates (Top), Random Effects Estimates (Middle) and Fit Indices (Bottom) for Models of the Predictors of Latvian Secondary School Students' Occupational Expectations

Parameter	M_{00}	M_{01}	M_{02}	Maternal model
		Fixed effect (unstandardized coefficient)		
Intercept (γ_{00})	-59.45	91.90***	-83.90*	-67.50*
PV1SCIE_w	.07***		.12***	.14***
ESCS_w		.34***	.47***	.49***
BMMJ1_w				.11***
PV1SCIE_b	.32***		.37***	.32***
ESCS_b		.28	.79	.77
		Random effect (unstandardized coefficient)		
Intercept (τ_{00})	336.49**	490.25***	302.40*	321.38**
Residual (σ^2)	11171.94***	11030.67***	10844.76***	10809.40***
		Model fit		
LL	-34692.85	-31702.87	-48995.76	-48828.32
AIC	69395.70	63415.73	98005.51	97672.63
BIC	69425.42	63445.45	98047.12	97720.19
R^2_within level	.01	.02**	.03***	.04***
R^2_between level	.33***	.01	.39**	.35***

No HYP_A or HYP_B was found. The equation summarizing the generative mechanism of Latvian students' BSMJ was:

$$Y_{ij} = -59.45 + 0.32PV1SCIE_{\_b} + 0.07PV1SCIE_{\_w} + (336.49 + 11171.94)$$

PV1SCIE_b was the dominant predictor to explain the between-level variance of BSMJ. Increasing students' mean PV1SCIE of a school could promote its students' mean BSMJ.

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Discussion

Previous research identified four categories of determinants of students' BSMJ. In the social environment domain, gender was a crucial factor influencing students' BSMJ (Korupp et al., 2002a; Marks, 2010; Sikora & Saha, 2009). This research found that gender was not a powerful predictor of students' BSMJ as it used to be. A simple linear regression method did not detect gender as a strong predictor in Lithuanian and Latvian samples. In the Estonian sample, gender was the fifth strong predictor but only can explain the 4.24% variance of students' BSMJ. Besides, in any Baltic country, the two-level latent covariate modeling could not incorporate gender in the equation. In the individual domain, learning achievement was a crucial predictor of students' high occupational expectations (Marks, 2010; Wicht & Ludwig-Mayerhofer, 2014). This research found science learning achievement was the most important predictor of students' BSMJ in a simple linear regression method. In the family domain, parents' occupational status and socio-economic status were the predictors of students' BSMJ (Croll, 2008; Hout, 2018; Mann et al., 2020; Tsukahara, 2007). This research would not question it in a single-level analysis, but advance it in a two-level analysis framework. In the school system domain, school types, immigrants in schools, and career guidance provided by schools were the predictors of students' BSMJ (Mann et al., 2020; Wicht, 2016; Wicht & Ludwig-Mayerhofer, 2014). There were student-teacher ratios, the total enrollment at school, and the shortage of education staff found by this research as other determinants of students' BSMJ.

This research furthered existing studies in two ways. First, depending on the developed statistical techniques, namely multi-level analysis, it distinguished the results at the within-group and between-group levels. A multi-level analysis is superior to single-level analysis because it avoids ecological fallacy and atomistic fallacy (Hox, 2010, p. 3). Second, it integrated four categories of determinants of students' BSMJ by PISA datasets. In sum, this research was a holistic exploration. It depicted a superordinate framework explaining the generative mechanism of students' BSMJ.

For exploring the generative mechanism of students' BSMJ, this research used two categories of baseline models. The conventional, maternal, power, individual, and joined models corresponded to the primary concern of this research. They were theoretical baseline models. M_{00}~M_{02} were constructed based on the fact that PV1SCIE and ESCS were the top two powerful predictors of students' BSMJ in the single-level analysis. They were technical baseline models.

For the conventional, maternal, power, individual, and joined models, the individual and joined models fitted data the worst or could not be constructed in any Baltic countries. It was a sign that the additive model was unsuitable for explaining the generative mechanism of students' BSMJ. The power model and the maternal model stood for the generative mechanism of Lithuanian and Estonian students' BSMJ, respectively. In the Lithuanian sample, keeping other predictors constant, one unit increase in HISEI_w led to a 0.52 unit increase in students' BSMJ; one unit increase in HISEI b led to a 0.50 unit increase in a school's students' average BSMJ. Nevertheless, HISEI was not a dominant predictor of Lithuanian students' BSMJ due to it could only explain the limited variance of BSMJ at the within-level and between-level. In the Estonian sample, keeping other predictors constant, one unit increase in BMMJ1_w led to a 0.68 unit increase in students' BSMJ; and one unit increase in BMMJ1_b led to a 0.85 unit increase in a school's students' average BSMJ. BMMJ1 was a dominant predictor of Estonian students' BSMJ as its explanatory power was great than the other predictors. In a two-level analysis framework, the relationship between parents' occupational status and children's BSMJ was not reproduced in the Latvian sample.

Students' science learning achievements played a significant role in forming students' BSMJ. In a single-level analysis framework, PV1SCIE was the most important predictor for explaining students' BSMJ of the Baltic countries. Nevertheless, the determinant coefficients of PV1SCIE ranged from .0778 to .1471, so PVISCIE's function on BSMJ also should not be exaggerated. In a two-level analysis framework, the generative mechanism models for the Lithuanian and Estonian samples excluded PV1SCIE in the equations. Although the PV1SCIE was included in the equation of the Latvian model, PV1SCIE had no explanatory power on the student-level variance of BSMJ.

Conclusions and Implications

This research focus on the roles of parents' occupational status and science learning achievement played on students' BSMJ in the Baltic countries. The single-level analysis showed common characteristics of the generative mechanisms of students' BSMJ in the Baltic countries. Students' learning achievements, parents' occupational status, and variables related to parents' occupational status (e.g., ESCS, HOMEPOS) stood for the formation elements of students' BSMJ. However, the two-level latent covariate modeling showed the differences in the generative

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mechanisms of students' BSMJ in the Baltic countries. The powerful model, the maternal model, and the science learning achievement pattern turned out to be the generative mechanism of students' BSMJ of Lithuania, Estonia, and Latvia, respectively.

This research supplied protocols for students of the Baltic countries to improve their occupational expectations. In Lithuania, improving a family's economic, social and cultural status or the highest parental occupational status could increase children's occupational expectations. A decrease in the student-teacher ratio and increase in student enrollment also would benefit the promotion of students' occupational expectations. In Estonia, improving a mother's occupational status and alleviating the shortage of education staff could improve children's occupational expectations. Since a big student-teacher ratio was associated with the shortage of education staff, there were similarities of the school system determinants in Lithuanian and Estonian samples. In Latvia, it was students' science learning achievements distinctly connecting to their occupational expectations.

This research had three implications. First, there was no need for fathers and mothers both holding high occupational status to achieve their children's high-skilled occupational expectations. In fact, one of the parents possessed better occupation would be enough, the generative mechanism of students' BSMJ of Lithuania expressed it clearly. Furthermore, it would be better the mother was the higher occupational status parent. The generative mechanism of students' BSMJ of Estonia has told it. Second, it highlighted the importance of strengthening adult education, especially that aimed at families with both parents of low occupational status. Third, this research disapproved of a mother being a full-time housewife. It may impede her children from having ambitions for high-skilled jobs.

The generative mechanism model is suitable for abundant situations. For example, with science learning achievements as outcome variables, the textbook usage as the primary concern, whether or not the textbook usage played a dominant role in science learning achievement can be investigated. Besides the textbook usage, what outstanding factors are involved in students' science learning achievements? If answers are available, then protocols can be constructed to improve students' science learning achievements.

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Declaration of Interest

Authors declare no competing interest.

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