



Abstract. *Although much research has explored the personal, family, school, and social influences on adolescents' career expectations, little is known about the types of family-related career expectations of students and career expectation contexts in school. Using PISA 2018 test data, a multi-level latent profile analysis was conducted with indicators of parents' occupational status and children's career expectations.*

This research found that family-related career expectations of Estonian secondary school students can be divided into three types: enterprising, resilient, and disengaged. At the organizational level, contexts for career expectations in schools can be classified as enterprising, enterprising and resilient composite, and disengaged and resilient composite types.

The research also found that science achievement and gender predicted latent profile memberships at the individual level.

It is proposed that to value the science curriculum and its teaching is to invest in future human resources. It is suggested that families and schools should pay attention to stimulating male students' career aspirations. The career expectation types of secondary school students within and between schools are of great significance to the construction of national human resources, the development of schools, and the research of families.

Keywords: *career expectation types, multilevel latent profile analysis, PISA 2018 datasets, variations between schools, science achievement*

Tao Jiang, Ji-gen Chen
Taizhou University, China
Ping-chuan Xu
China West Normal University, China
Ping-fei Zeng
Zhejiang Normal University, China



MULTILEVEL LATENT PROFILE ANALYSIS OF ESTONIAN SECONDARY SCHOOL STUDENTS' CAREER EXPECTATIONS WITH SCIENCE ACHIEVEMENT AND GENDER AS COVARIATES

**Tao Jiang,
Ji-gen Chen,
Ping-chuan Xu,
Ping-fei Zeng**

Introduction

Children develop career aspirations through family upbringing and school education. Failure to form career expectations based on their interests and specialties in school can harm personal development. There is a high probability that the lack of clear career expectations in adolescence will lead to a long period of unemployment or short-time, low-paid jobs after leaving school (Schmitt-Wilson & Faas, 2016; Sikora, 2018). In the past two decades, the rapid development of electronics, computers, and artificial intelligence has caused profound changes in the structure of human resources. Machines are increasingly replacing people in some traditional occupational fields, such as vending machines replacing supermarket clerks and numerically-controlled machine tools replacing industrial workers. However, it is hard to imagine some highly skilled jobs being replaced by machines. Machines, for example, teach human children instead of teachers or treat human diseases instead of doctors. Society, therefore, wants the younger generation now to have career aspirations for high-skilled jobs. It makes them more likely to have access to jobs when they reach adulthood. Furthermore, the labor market does not want to see a difference in the career aspirations of young men and women for high-skilled jobs; low career aspirations on either side will result in a loss of human resources.

Literature Review

There are several theoretical frameworks for career expectation research, such as pipeline theory, social cognitive theory, social learning theory, and social cognitive career theory (Bandura et al., 2001; Blickenstaff, 2005; Krumboltz, 1994; Lent et al., 1994). Based on different theoretical frameworks, predictors of adolescents' career expectations are examined using techniques such as single- or multilevel regression or structural equation modeling (Schoon & Parsons, 2002; Tsukahara, 2007).

Gender has been widely studied as an influential factor in career expectations. The first is the study of gender differences in career orientation. Fathers' occupations have a significant impact on their sons' career aspirations, while mothers' occupations have a strong influence on their daughters' career aspirations (Korupp et al., 2002; Tsukahara, 2007). Boys tend to enter enterprising professional fields such as computers, engineering, and mathematics, while girls prefer careers related to art, nursing, agronomy, and biology (Holland, 1997; Korupp et al., 2002; Sikora & Pokropek, 2012). With the rapid development of society, this gender difference in career orientations is diminishing but not disappearing (Sikora & Saha, 2009). The second is a study of gender differences in the level of career ambition. A survey of more than 3,000 adolescents in 42 American states has shown that half want low-specialized jobs, but only one-sixth of them are available in the labor market (Hoff et al., 2022). Social development has led to an increasing specialization of jobs. Therefore, a highly skilled occupation is consistent with the well-being of individuals, families, and society. Using data from the PISA 2000 test, Marks (2010) found that female students' career expectations are higher when compared with male students. The same pattern has been replicated in several studies (Al-Bahrani et al., 2020; McDaniel, 2010). However, girls' higher career expectations may not always translate into future advantages in the job market. Existing research has found that some ambitious secondary school students do not attend college or do not study hard once there, leaving them unemployed or in low-paying jobs that do not meet their expectations at the age of 26 (Kim et al., 2019; Schmitt-Wilson & Faas, 2016).

Another factor that has attracted much attention is academic achievement. Students who do well in science and mathematics tend to have higher career aspirations (Al-Bahrani et al., 2020). Science and mathematics achievements in secondary school significantly influence youngsters' choice of major in STEM when they enter college (Sikora & Pokropek, 2012; Tai et al., 2006). However, some research has indicated that some college students who major in STEM did not do well in mathematics or did not take pre-college courses like calculus during their secondary school period (Cannady et al., 2014). Furthermore, recent research has also found that career aspirations are unstable and vary with academic performance (Carolan, 2017). Changes in academic achievement significantly impact students from low-income families and boys to change career expectations (Carolan, 2017; Karlson, 2019).

Parents enlighten children's recognition of occupations. Their educational levels and occupational status influence their children's occupational expectations (Al-Bahrani et al., 2020; Lee & Byun, 2019). Some studies have suggested that mothers' employment status affects their children's occupational expectations strongly, and it is necessary to provide low-educated mothers with the opportunity to receive additional vocational education (Augustine, 2017; Kalmijn, 1994; Korupp et al., 2002). Nevertheless, some studies argue that the father's occupational status has a more powerful guiding effect on offspring (Tsukahara, 2007). Other studies suggest that the father's and mother's occupational status together is integral in shaping their children's career expectations (Hout, 2018; Kleinjans, 2010). In recent years, a few studies have examined the reasons parents influence children's career expectations. The most mentioned reasons include parental values, material provision for their children's schooling, evaluation of their children's academic abilities, and parental attitudes towards particular academic fields, such as science (DeWitt et al., 2011; Jodl et al., 2001; Schoon & Parsons, 2002).

In addition to the family, school is another important place where children are socialized to form career expectations (Bozick et al., 2010). First, the type of school has an enormous influence on career expectations. Few would oppose that academic secondary school students' career aspirations are higher when compared with vocational secondary school students (Lee & Byun, 2019; Wicht & Ludwig-Mayerhofer, 2014). Second, experiences in school have a significant impact on career aspirations. Students more attuned to their schools have higher career expectations (McDaniel, 2010). Less discriminatory experiences at school help disadvantaged students develop positive career expectations (Wicht, 2016). Third, human resources in schools have a significant impact on career expectations. Teacher shortages can result in low career aspirations for students (Jiang et al., 2021). Teachers' unfamiliarity with the college application process can lower secondary school student's career aspirations (Roderick et al., 2011). The career planning that teachers make for students affects their career aspirations, and adolescents from low socioeconomic status families especially suffer from a lack of such career planning guidance (Holland & DeLuca, 2016; Rowan-Kenyon et al., 2011).

In exploring the factors influencing children's career expectations, existing studies have used variable-centered methods such as questionnaires, interviews, hierarchical linear models, multilevel regression, and structural equation modeling (Andersen & van de Werfhorst, 2010; Bandura et al., 2001; Bigler et al., 2003; Jodl et al., 2001; Korupp et al., 2002). There are no studies on secondary school students' career expectations based on a person-centered methodology. The variable-centered method finds predictors of career expectations, whereas the person-centered approach aims to find the types of career expectations among students and schools.



Research Focus

This research focused on the types of career expectations of Estonian secondary school students. The Estonian secondary school was used as an example because its sampling error was well controlled (see the following sub-chapter “samples” for details). Parents have an irreplaceable role in guiding the formation of their children's career expectations. The occupations of mothers and fathers influence the career choices of their children (Hout, 2018; Korupp et al., 2002; Tsukahara, 2007). Therefore, this research constructed the career expectation types of secondary school students related to their parents' career status. In this way, the intergenerational transmission of careers can be more clearly examined, and a more accurate picture can be obtained of the proportion of students who aspire to be more ambitious beyond the constraints of their family of origin.

This research also looked at the context of career expectations in Estonian schools. Parents interfere with their children's educational outcomes by choosing schools for them, while the government intervenes in families' school choice behavior through educational policies to avoid severe isolation. In an idealized, non-divided school system, the proportion of students of various career expectation types is approximately equal. In heavily isolated school systems, secondary school students of different career expectation types attend disparate schools. The present research constructed types of career expectations in Estonian schools, which can examine the integration of students of different vocational expectation types in schools.

Individual- and school-level covariates were also included in the multilevel latent profile modeling in this research to examine the impact of these variables on latent profile membership. Given that studies have shown that children who do well in science and girls have higher career aspirations, two covariates—gender and science achievement—were set at level 1. Therefore, whether they influenced individuals' latent profile affiliation can be examined. Studies have shown that the greater the shortage of human resources in schools, the lower the career expectations of Estonian secondary school students (Jiang et al., 2021). Therefore, teacher shortage was set as a covariate at level 2 to examine whether it affected the schools' latent profile membership.

Research Aim and Research Questions

Figure 1 presents the research aims: to establish the types of family-related career expectations of secondary school students and to understand the impact of gender, science achievement, and school human resources on latent profile membership.

Figure 1

Multilevel Regression Mixture Model with Individual- and School-level Covariates

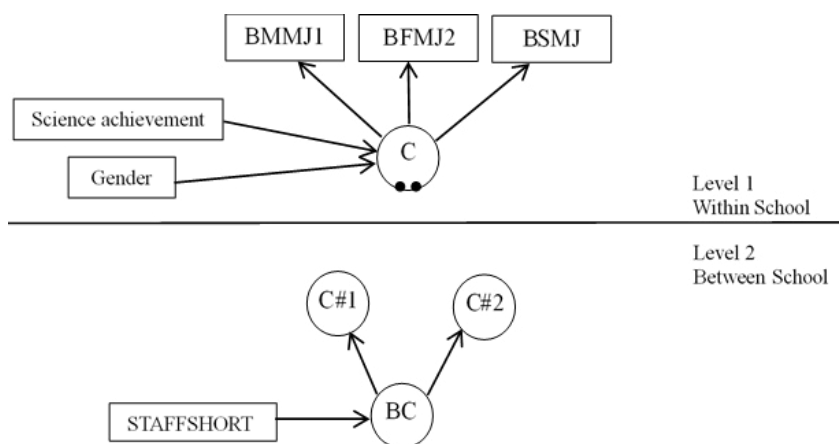


Figure 1 presents the three latent profile indicators of BMMJ1, BFMJ2, and BSMJ. They were the mother's occupation, the father's occupation, and the son's (or daughter's) occupational expectations, respectively (OECD, 2020a; OECD, 2020b). The data for these three latent profiles and the two covariates of science achievement and gender were recorded in the PISA 2018 student dataset (OECD, 2020b). Data for the level 2 covariate, human re-

source shortage (STAFFSHORT), can be found in the PISA 2018 school dataset (OECD, 2020b). If secondary school students' career expectations are divided into three types at the within-school level, there are two random means, C#1 and C#2. BC is the latent profile defined by C#1 and C#2 at the school level, and C#1 and C#2 are continuous latent variables that vary between schools (Flunger et al., 2021; Henry & Muthén, 2010; Mäkikangas et al., 2018).

The research questions were:

1. At the individual level, what career expectation types were there for secondary school students?
2. At the organizational level, was there an aggregation of identical career expectations?
3. Were science achievement, gender, and school staff resources predictors of membership in latent profiles of career expectations?

Understanding the distribution of career expectations among students and schools is a central aspect of a country's human resources development and has important implications for school development and family research.

Research Methodology

General Background

For a long time, on the research topic of career expectations, people's research interest has focused on finding its predictors, thus adopting various variable-centered analysis techniques. Latent class/profile analysis is a person-centered analysis technique (Marsh et al., 2009). It aims not to discover associations between variables but to group people according to their different characteristics of variables. If the indicators used for grouping are categorical variables, the technique is called latent class analysis (Marsh et al., 2009; Nylund et al., 2007). Latent profile analysis is required if the indicators are continuous variables (Chung et al., 2020). Since people are often in communities or organizations, and given the nested structural nature of the data, multi-level latent class/profile analyses (MLCA/MLPA) have been developed in the last decade (Henry & Muthén, 2010; Mäkikangas et al., 2018).

Henry and Muthén (2010) used the MLPA to classify female students into heavy, moderate, and light smokers and examined how the proportion of the three smoking types varied across communities. Mäkikangas et al. (2018) grouped college staff by their level of work stress and explored how the percentage of different groups varies by the college sector. Flunger et al. (2021) categorized students according to their homework behavior and examined the differences in homework behaviors in class situations. The multilevel latent profile analysis was divided into two types of parametric and non-parametric models. In all three of the above studies, grouping was done at levels 1 and 2, distinguishing between different organizational contexts, and was a non-parametric model. Based on the non-parametric MLPA model, this research included level 1 and level 2 covariates, which was a multilevel regression mixture model (Flunger et al., 2021; Henry & Muthén, 2010; Mäkikangas et al., 2018).

Several indexes are used to select the best latent profile solutions (Collins et al., 1993; Loken & Molenaar, 2008; Marsh et al., 2009; Nylund et al., 2007). Among these indexes, Henry and Muthén (2010) highlighted the Bayesian Information Criterion (BIC), entropy, and posterior probabilities as the basis for the selection. Generally, as profiles become smaller, the information criterion decreases, and the classification accuracy increases. However, if it is accompanied by a profile share of less than 2% and similar profiles, the increase in classification accuracy is due to over-extraction (Chung et al., 2020; Marsh et al., 2009). As a result, Mäkikangas et al. (2018) emphasized change speed rather than BIC size as the primary criterion for selection. If both latent profile solutions have good goodness of fit, scholars recommend choosing the one with fewer profiles (Loken & Molenaar, 2008; Marsh et al., 2009).

Sample

5316 Estonian students aged 15 in 230 schools took the PISA 2018 test (Jiang et al., 2021; data missing for two schools numbered 82 and 208). A value of 17 was assigned to BMMJ1 and BFMJ2 if the parent was currently in educational training, retired, or doing housework (OECD, 2020b). Missing value records for BMMJ1, BFMJ2, and BSMJ were 774, 1095, and 1170, respectively. Missing data on BMMJ1 and BFMJ2 were due to the child not knowing, being unwilling to report, being from a single-parent household, etc. (OECD, 2020b). Some reasons led to BSMJ data being missing. They were the absence of career expectations, inconsistency between interest-based and survival-need-based career expectations, instability of career expectations, and reluctance to report their career expectations. Including missing data in the modeling can leave the results uninterpreted due to uncertainty about the reasons for the missing data. Therefore, missing data were excluded from the MLPA. There is no accepted standard for the



minimum sample size required for MLPA (Mäkikangas et al., 2018). The multilevel analysis empirical standard is adopted, which is not fewer than 100 communities and not fewer than ten people per community (Hox, 2010, p. 235; Silva et al., 2020, p. 38). After removing records containing missing data, then removing schools with fewer than ten records, the final dataset consisted of 2,816 students in 145 schools. It was approximately 19.4 students per school. According to the PISA project team, in 2018, there were 12,257 people aged 15 in Estonia, 12,120 of them attending secondary schools, and 5,316 taking the PISA test (OECD 2019, p. 228). Therefore, 2,816 people account for 23.2% of the total 15-year-old people enrolled in secondary schools, which was a good representation of the overall population.

Data Analysis

The 2816 students had no missing values for the variables of science achievement and STAFFSHORT. The descriptive statistics for BMMJ1, BFMJ2, and BSMJ are shown in Table 1.

Table 1
Descriptive Statistics for Latent Profile Indicators

Statistics	Analytic sample ^a			Original sample ^b		
	BMMJ1	BFMJ2	BSMJ	BMMJ1	BFMJ2	BSMJ
Mean	49.81	45.86	66.41	48.44	44.38	64.72
Minimum	11.56	11.56	11.56	11.56	11.01	11.56
Maximum	88.96	88.70	88.96	88.96	88.96	88.96
Percentiles	25	28.48	28.52	51.92	26.80	26.85
	50	54.55	37.83	74.66	51.56	35.34
	75	68.75	65.12	80.46	68.55	65.01

Note. a. $n = 2816$ students. b. $n = 5316$ students.

According to the analytic sample on the left-hand side of Table 1, the occupational status of fathers and mothers of Estonian students does not differ significantly in the lower quartile. Nevertheless, the upper quartile, the median, and the mean values for BMMJ1 were more than the corresponding values for BFMJ2. It suggested that for parents whose occupational status was above 25%, mothers had some advantage over fathers in terms of occupational status. The lower quartile of students' career expectations was already 51.92, and the median was 74.66, indicating that students generally had high career aspirations. According to the original sample column on the right-hand side of Table 1, the total data set shows the same pattern.

The gender differences in BMMJ1, BFMJ2, and BSMJ are shown in Table 2.

Table 2
The Gender Difference t-test of Latent Profile Indicators

Indicators		n	M	Equal variance	t	p (2-tailed)
Analytic sample	BMMJ1	Female	1478	50.00	Assumed	.49
		Male	1338	49.60		
	BFMJ2	Female	1478	45.21	Not assumed	-1.79*
		Male	1338	46.57		
	BSMJ	Female	1478	70.24	Not assumed	11.25***
		Male	1338	62.19		



Indicators		<i>n</i>	<i>M</i>	Equal variance	<i>t</i>	<i>p</i> (2-tailed)
Original sample	BMMJ1	Female	2349	48.28	Assumed	.51
		Male	2193	48.62		
	BFMJ2	Female	2147	43.83	Not assumed	-1.83*
		Male	2074	44.96		
	BSMJ	Female	2122	68.25	Not assumed	11.71***
		Male	2024	61.03		

Note. * $p < .1$, *** $p < .001$.

According to Table 2, in the analytic sample, there is no gender difference for BMMJ1. The gender difference test for BFMJ2 suggested marginal significance, with male students' fathers having slightly higher occupational status than female students' fathers. The gender difference for BSMJ was significant, with female students having much higher career expectations than male students. The same pattern was observed in the original sample.

Instrument and Procedures

The PISA project team used student questionnaires to obtain information on gender, BMMJ1, BFMJ2, and BSMJ, while data on STAFFSHORT was obtained through school questionnaires (OECD, 2020b).

The MLPA of this research required the establishment of four models. The first model was a single-level LPA; the second was a parametric model with K-1 random intercepts; the third was a non-parametric MLPA model; and the fourth was a multilevel regression mixture model with covariates (Henry & Muthén, 2010; Mäkikangas et al., 2018; Vermunt, 2003). Model 2 was the simplest type of MLPA. K was the number of career expectation profiles found in model 1. Model 2 was designed to determine whether there were different career expectation contexts at the school level rather than how many there were. Model 3 set up latent profiles at the school level. Model 4 examined the effect of covariates on membership of the latent profiles. MLPA was performed with Mplus 7.4.

Research Results

Types of Career Expectations at the Student Level

At the student level, solutions from two to eight profiles were tried. According to Table 3, BIC decreases significantly from the two-profile to five-profile, especially from the two-profile to three-profile solution. Subsequently, from the five-profile to the eight-profile solution, the trend of BIC reduction became flat. As far as BIC was considered, the three-profile to five-profile solutions were considered good. From the perspective of classification accuracy indexes: entropy and lowest posterior probability, the four-profile solution was not good at classification accuracy. The students were correctly classified into each profile by the three-profile and five-profile solutions. However, the deceleration of the BIC of the five-profile solution was significantly lower than that of the three-profile solution, and a small profile of only 4.2% appeared. In addition, the five-profile solution did not hold up in either model 3 or model 4, so the three-profile solution won out for its parsimony.

Table 3
Model Fit Indexes of Latent Profile Solutions for Estonian Sample (Model 1)

Solutions	Fit statistics		
	BIC	Entropy	Lowest posterior probabilities
2 profiles	73279.93	.94	.98
3 profiles	72522.89	.95	.98
4 profiles	72073.77	.91	.84



Solutions	Fit statistics		
	BIC	Entropy	Lowest posterior probabilities
5 profiles	71675.26	.96	.96
6 profiles	71526.17	.92	.87
7 profiles	71246.91	.88	.83
8 profiles	71073.44	.89	.86
Conditional means_BMMJ1-BFMJ2-BSMJ (Proportions)			
The three-profile solution			
58.2-65.7-72.7 (42.7%)	44.9-29.1-72.3 (43.4%)	38.9-36.4-27.8 (13.9%)	
The five-profile solution			
36.3-28.8-29.6 (11.7%)	48.9-44.9-50.9 (8.7%)	45.9-29.9-76.1 {39.4%}	58.7-67.1-75.6 {36%}
			48.9-62.3-31.3 {4.2%}

Note. $n = 2816$ students. Index values that suggest the profile solution is desirable are shown in bold.

Based on the three-profile solution, students were divided into three types of career expectations: enterprising, resilient, and disengaged. The enterprising group, at 42.7%, had high career expectations and parental career status. The resilient group, at 43.4%, had a significantly lower occupational status of mothers than the enterprising group but had a higher career status relative to the male partner in the family. This group of students also had high career expectations. The disengaged group, at 13.9%, had a further lower occupational status for mothers than the resilient group and was close to that of the male partner in the family. This group of students had low career expectations. Enterprising meant students pursuing a high career status similar to their parents. The resilient profile was named because this group of students transcended the limits of their family's existing occupations to pursue higher career status. The disengaged profile got its name because this group of students identified with the low-skilled careers of their families and therefore were detached from the demands of the competitive job market they would face as adults.

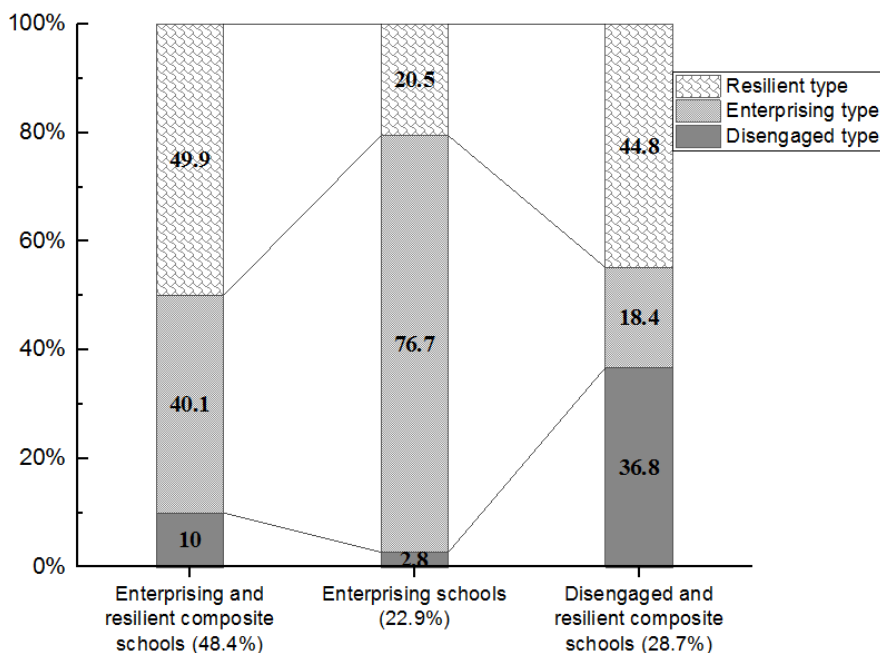
Types of Career Expectation Contexts at School Level

Since career expectations were divided into three profiles at the student level, two random means, C#1 and C#2, were set at the school level. For Model 2, BIC = 72688.91, lowest posterior probability = .909, entropy = .894 (variance estimate for C#1 = 1.035, $SE = .181$, $p < .001$; variance estimate for C#2 = .115, $SE = .066$, $p = .081$). It showed that the typicality of high or low career expectations of secondary school students varies across schools. Namely, several school contexts existed, and the proportions of the three Level 1 profiles were significantly different across schools.

Model 3 can be exercised as long as model 2 holds. The best non-parametric model was at the school level, classifying schools into three contexts. The model had a BIC of 72678.88, the lowest posterior probability of .781, and entropy of .813. The classification results of career expectations at the student and school levels are shown in Figure 2.



Figure 2
Three School-level Career Expectation Contexts (Model 3)



The enterprising and resilient composite school consisted mainly of enterprising and resilient profiles at level 1. The enterprising school mainly consisted of level 1 student groups of high BMMJ1-BFMJ2-BSMJ. The disengaged and resilient composite school was named because it was mainly composed of disengaged and resilient student groups at level 1. The proportions for the three school types were 48.4%, 22.9%, and 28.7%, respectively.

Among the enterprising and resilient composite school contexts, the proportions of disengaged, enterprising, and resilient profiles at level 1 were 10%, 40.1%, and 49.9%, respectively. In an enterprising school context, the proportion of the level 1 enterprising profile was 76.7%. It accounted for a much large proportion than the resilient or disengaged profile. Among the disengaged and resilient composite school contexts, the disengaged, resilient, and enterprising profiles on level 1 accounted for 36.8%, 44.8%, and 18.4%, respectively.

There were 495 enterprising students in the enterprising school system, compared to 547 and 149 in the two compound school systems. Thus, they were more numerous in compound school systems. Resilient students were the largest group in the composite school context, and even in enterprising school contexts, they accounted for one in five (20.5%, $n = 132$). Disengaged students were concentrated mainly in composite school contexts.

Effect of Covariates on Membership of Latent Profiles

The BC(3)C(3) setting fitted the data well when the two covariates, gender and science achievement, were set at Level 1 (BIC = 72003.907, entropy = .799). In this case, no profile switching occurred at either level 1 or level 2.

Covariates can be set at level 2, and the complexity of the model increases. There were two covariates to choose from: STAFFSHORT and the group mean of students' science achievements. At level 2, when the group mean of science achievement was a covariate, the entropy value increased to .875, BIC = 72058.374. While no profile switching occurred at level 1, profile switching occurred at level 2. At level 2 with STAFFSHORT as a covariate, there was an entropy of .8 and a BIC of 72019.335. No profile switching occurred at either level 1 or level 2. As a result, the multilevel latent profile model with gender and science achievement as covariates at Level 1 and STAFFSHORT as a covariate at Level 2 fitted the data (i.e., Model 4; see Figure 1).

The model showed that the better students did in science, the more likely they were to belong to the enterprising profile (estimate = .012, $SE = .001$, $p < .001$). Besides, the probability of a student belonging to the resilient profile increased with good science achievement (estimate = .007, $SE = .001$, $p < .001$). The model also showed that



male students were less likely to belong to the enterprising profile than female students (estimate = $-.866$, $SE = .131$, $p < .001$). Male students were also less likely than female students to belong to the resilient profile (estimate = -1.086 , $SE = .12$, $p < .001$). The model also showed that the level 2 covariate STAFFSHORT did not predict membership in the level 2 enterprising profile (estimate = $.18$, $SE = .367$, $p = .624$). STAFFSHORT also did not forecast the membership in the level 2 enterprising-resilient composite profile (estimate = $.203$, $SE = .412$, $p = .622$).

Discussion

The role of mothers in shaping their children's career expectations should not be overlooked. Parents' careers affect the career aspirations of their offspring (Al-Bahrani et al., 2020; Bozick et al., 2010; Lee & Byun, 2019). Some studies have highlighted the role of mothers in guiding career aspirations (Augustine, 2017; Korupp et al., 2002). This research found that families with the lowest maternal occupational status also had children with the lowest career expectations. Therefore, mothers who strive for higher occupations rather than stay at home are more conducive to children developing positive occupational attitudes.

Gender predicted latent profile membership. Females were more likely than male secondary school students to be in the enterprising or resilient profile, given the same parental occupational status. It supported those studies that suggest female teenagers have higher career expectations (Al-Bahrani et al., 2020; Marks, 2010; McDaniel, 2010). Therefore, in a family, mothers need to be as concerned with guiding the career aspirations of their sons as they are with orienting the career aspirations of their daughters. Alternatively, the father in the family needs to be more involved in their son's career planning.

Science achievement predicted membership in level 1 enterprising and resilient profiles. This finding supported those studies that argue that students who do well in science tend to have higher career aspirations (Sikora & Pokropek, 2012; Tai et al., 2006). It thus turns out that to value the science curriculum and its teaching is to invest in the future human resources of the country.

The between-school variation in career expectations was not predicted by staff shortages. At the student level, teachers' ability to plan their students' careers influences teenagers' career aspirations (Holland & DeLuca, 2016; Roderick et al., 2011; Rowan-Kenyon et al., 2011). A two-level analysis also shows that STAFFSHORT predicts career expectations at the school level (Jiang et al., 2021). This research found that educational staff shortages do not forecast the schools' career expectation profiles. This finding is not an argument against previous studies. Under the technical framework of MLPA, this finding meant that STAFFSHORT did not predict the type of career expectation at level 2. In other words, the membership of the level 2 profile cannot be judged according to STAFFSHORT.

Person-centered MLPA is an exciting and promising analytical technique. For the first time, this research linked students' career expectations to their parents' career status and identified types of career expectations at the student and school levels. Rather than the isolated school contexts of enterprising, resilient, and disengaged, the school contexts found in this research were predominantly composite. 77.1% of students lived in compound school contexts.

The model could not fit the data when the science achievement group mean was used as a level 2 covariate. It impeded testing whether the group mean of science achievement affects membership in the Level 2 latent profiles. If this model can be established in subsequent studies, it will clarify the effect of science achievement on latent profile membership at the between-school level. The effect of the level 2 covariate STAFFSHORT on between-school latent profile membership was also not found in this study. The above were non-parametric models. Within the framework of the parametric model, it is possible to test the effect of STAFFSHORT on within-school latent profile membership (Henry & Muthén, 2010). However, this parametric model also failed to fit the data. In conclusion, this study had limitations in testing the effects of the level 2 covariates (science achievement group means and STAFFSHORT) on career expectation profile membership at the within-school and between-school levels.

Conclusions and Implications

At the student level, enterprising, resilient, and disengaged career expectation types were found among Estonian secondary school students. The proportion of students in the resilient group was much larger than in the disengaged group (43.4% vs. 13.9%). The enterprising and disengaged profiles were reflections of the intergenerational transmission of careers. On the other hand, the resilient profile was a signal to break through the intergenerational transmission of occupations. There was no severe aggregation of career expectations (that



is, the isolation of different career expectations). No disengaged school contexts were found, so the low career expectations student group was not isolated. Aggregation was mainly found in the second school context, i.e., the enterprising school context, where 22.9% of students were in this organizational climate. Its main body was the enterprising student group, accounting for 76.7%. Most students (77.1%) were in a composite school context that promotes integration and socialization. Nearly half of the students (48.4%) were in enterprising and resilient compound schools, an organizational climate in which parents had varying levels of career status, but most students had high career expectations. The study also found that gender and science achievement predicted latent profile membership at the student level, while staff shortages did not predict latent profile membership at the school level.

This research had three new developments. First, it found the predictive effect of science achievement on the career expectation types of secondary school students at the within-school level. Second, maternal influence was discovered to characterize the career expectation types of secondary school students. The mother's moderate but higher occupational status than the father's increased the probability that the offspring belonged to the resilient profile. Meanwhile, the mother's and father's low-skilled careers raised the possibility that the offspring belonged to the disengaged profile. Third, it found gender differences in the types of career expectations of students. Female students had a better chance of belonging to the enterprising and resilient profiles than male students. Thus, this research complemented the findings of the existing variable-centered methodology with the results of the person-centered one.

This research provides the following implications. Teachers should further improve students' participation in science courses. Achieving good science achievement increases the chances of students entering resilient and enterprising profiles. Because there is a close association between the low occupational status of mothers and their children belonging to the disengaged profile, society needs to focus on providing educational training and employment opportunities for mothers who are unemployed or currently doing housework. Schools should offer career planning guidance for students. Career planning teachers should also help secondary school students understand the trajectory of higher education that is consistent with their career aspirations. In this way, the highly skilled career aspirations of 15-year-old students have a better chance to transform into their adult career status. In addition, society, schools, and families must not neglect career planning guidance for young men. Today's young men are not only the workforce in the future but also the fathers of a family in the future. The pursuit of higher occupational status by young men will help to gradually reverse the trend where the fathers' mean and median occupation status is lower than those of mothers.

Further research should distinguish more precisely the types of students' career expectations. For example, by adding latent profile indicators, it is possible to test whether two subtypes exist in the high-skilled career expectations of secondary school students: management-related and science-related. When these two subtypes hold in the student population, it is possible to test whether science achievement increases the odds of students achieving membership in a science-related subtype compared to a management-related subtype. Another research direction is to continue exploring career expectation contexts at the school level. Do schools exist that consist of mainly disengaged students? It reflects the intergenerational transmission of low occupational status. If such schools exist, what percentage of students attend them? These issues need to be answered. Going beyond career expectations, the MLPA model can be used to explore a wide range of educational questions. For example, by combining science learning behaviors, cognitive characteristics, and psychological characteristics (e.g., positive emotions), it is possible to test whether there are three groups of students with high, medium, and low levels of commitment to science courses. If the model holds, the researcher can know which cognitive and psychological traits the three groups carry.

Acknowledgements

This research is from the project (Grant number BGA210057) supported by the National Social Science Foundation of China.

Declaration of Interest

The authors declare no competing interest.



References

- Al-Bahrani, M. A., Allawati, S. M., Abu Shindi, Y. A., & Bakkar, B. S. (2020). Career aspiration and related contextual variables. *International Journal of Adolescence and Youth*, 25(1), 703–711. <https://doi.org/10.1080/02673843.2020.1730201>
- Andersen, R., & van de Werfhorst, H. G. (2010). Education and occupational status in 14 countries: The role of educational institutions and labour market coordination. *The British Journal of Sociology*, 61(2), 336–355. <https://doi.org/10.1111/j.1468-4446.2010.01315.x>
- Augustine, J. M. (2017). Increased educational attainment among U.S. mothers and their children's academic expectations. *Research in Social Stratification and Mobility*, 52, 15–25. <https://doi.org/10.1016/j.rssm.2017.08.001>
- Bandura, A., Barbaranelli, C., Caprara, G. V., & Pastorelli, C. (2001). Self-efficacy beliefs as shapers of children's aspirations and career trajectories. *Child Development*, 72(1), 187–206. <https://doi.org/10.1111/1467-8624.00273>
- Bigler, R. S., Averhart, C. J., & Liben, L. S. (2003). Race and the workforce: Occupational status, aspirations, and stereotyping among African American children. *Developmental Psychology*, 39(3), 572–580. <https://doi.org/10.1037/0012-1649.39.3.572>
- Blickenstaff, J. C. (2005). Women and science careers: Leaky pipeline or gender filter? *Gender and Education*, 17(4), 369–386. <https://doi.org/10.1080/09540250500145072>
- Bozick, R., Alexander, K., Entwisle, D., Dauber, S., & Kerr, K. (2010). Framing the future: Revisiting the place of educational expectations in status attainment. *Social Forces*, 88(5), 2027–2052.
- Cannady, M., Greenwald, E., & Harris, K.N. (2014). Problematising the STEM pipeline metaphor: Is the STEM pipeline metaphor serving our students and the STEM workforce? *Science Education*, 98(3), 443–460. <https://doi.org/10.1002/sce.21108>
- Carolan, B. V. (2017). Assessing the adaptation of adolescents' educational expectations: Variations by gender. *Social Psychology of Education*, 20(2), 237–257. <https://doi.org/10.1007/s11218-017-9377-y>
- Chung, G., Phillips, J., Jensen, T. M., & Lanier, P. (2020). Parental involvement and adolescents' academic achievement: Latent profiles of mother and father warmth as a moderating influence. *Family Process*, 59(2), 772–788. <https://doi.org/10.1111/famp.12450>
- Collins, L. M., Fidler, P. L., Wugalter, S. E., & Long, J. D. (1993). Goodness-of-fit testing for latent class models. *Multivariate Behavioral Research*, 28(3), 375–389. https://doi.org/10.1207/s15327906mbr2803_4
- DeWitt, J., Archer, L., Osborne, J., Dillon, J., Willis, B., & Wong, B. (2011). High aspirations but low progression: The science aspirations-careers paradox amongst minority ethnic students. *International Journal of Science and Mathematics Education*, 9(2), 243–271. <https://doi.org/10.1007/s10763-010-9245-0>
- Flunger, B., Trautwein, U., Nagengast, B., Lüdtke, O., Niggli, A., & Schnyder, I. (2021). Using multilevel mixture models in educational research: An illustration with homework research. *The Journal of Experimental Education*, 89(1), 209–236. <https://doi.org/10.1080/00220973.2019.1652137>
- Henry, K. L., & Muthén, B. (2010). Multilevel latent class analysis: An application of adolescent smoking typologies with individual and contextual predictors. *Structural Equation Modeling: A Multidisciplinary Journal*, 17(2), 193–215. <https://doi.org/10.1080/10705511003659342>
- Hoff, K., Van Egdome, D., Napolitano, C., Hanna, A., & Rounds, J. (2022). Dream jobs and employment realities: How adolescents' career aspirations compare to labor demands and automation risks. *Journal of Career Assessment*, 30(1), 134–156. <https://doi.org/10.1177/10690727211026183>
- Holland, J.L. (1997). *Making vocational choices: A theory of careers*. Psychological Assessment Resources.
- Holland, M. M., & DeLuca, S. (2016). "Why wait years to become something?" Low-income African American youth and the costly career search in for-profit trade schools. *Sociology of Education*, 89(4), 261–278. <https://doi.org/10.1177/0038040716666607>
- Hout, M. (2018). Americans' occupational status reflects the status of both of their parents. *Proceedings of the National Academy of Sciences of the United States of America*, 115(38), 9527–9532. <https://doi.org/10.1073/pnas.1802508115>
- Hox, J. J. (2010). *Multilevel analysis: Techniques and applications* (2nd ed.). Routledge/Taylor & Francis Group.
- Jiang, T., Chen, J.-G., & Fang, W. (2021). The generative mechanism of secondary school students' occupational expectations in the Baltic countries: Influence of family, school, and individual science learning achievement. *Journal of Baltic Science Education*, 20(5), 759–774. <https://doi.org/10.33225/jbse/21.20.759>
- Jodl, K. M., Michael, A., Malanchuk, O., Eccles, J. S., & Sameroff, A. (2001). Parents' roles in shaping early adolescents' occupational aspirations. *Child Development*, 72(4), 1247–1265. <https://doi.org/10.1111/1467-8624.00345>
- Kalmijn, M. (1994). Mother's occupational status and children's schooling. *American Sociological Review*, 59(2), 257–275. <https://doi.org/10.2307/2096230>
- Karlsen, K. B. (2019). Expectation formation for all? Group differences in student response to signals about academic performance. *The Sociological Quarterly*, 60(4), 716–737. <https://doi.org/10.1080/00380253.2019.1580549>
- Kim, S., Klager, C., & Schneider, B. (2019). The effects of alignment of educational expectations and occupational aspirations on labor market outcomes: Evidence from NLSY79. *The Journal of Higher Education*, 90(6), 992–1015. <https://doi.org/10.1080/00221546.2019.1615333>
- Kleinjans, K. J. (2010). Family background and gender differences in educational expectations. *Economics Letters*, 107(2), 125–127. <https://doi.org/10.1016/j.econlet.2010.01.002>



- Korupp, S. E., Ganzeboom, H. B. G., & van der Lippe, T. (2002). Do mother matter? A comparison of models of the influence of mother's and father's educational and occupational status on children's educational attainment. *Quality and Quantity*, 36(1), 17–42. <https://doi.org/10.1023/A:1014393223522>
- Krumboltz, J. D. (1994). Improving career development theory from a social learning theory perspective. In M. L. Savickas & R. W. Lent (Eds.), *Convergence in career development theory* (pp. 9–32). CPP Books.
- Lee, B., & Byun, S. (2019). Socioeconomic status, vocational aspirations, school tracks, and occupational attainment in South Korea. *Journal of Youth and Adolescence*, 48(8), 1494–1505. <https://doi.org/10.1007/s10964-019-01056-5>
- Lent, R. W., Brown, S. D., & Hackett, G. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. *Journal of Vocational Behavior*, 45(1), 79–122. <https://doi.org/10.1006/jvbe.1994.1027>
- Loken, E., & Molenaar, P. (2008). Categories or continua? The correspondence between mixture models and factor models. In G. R. Hancock & K. M. Samuelsen (Eds.), *Advances in latent variable mixture models* (pp. 277–297). Information Age Publishing.
- Mäkikangas, A., Tolvanen, A., Aunola, K., Feldt, T., Mauno, S., & Kinnunen, U. (2018). Multilevel latent profile analysis with covariates: Identifying job characteristics profiles in hierarchical data as an example. *Organizational Research Methods*, 21(4), 931–954. <https://doi.org/10.1177/1094428118760690>
- Marks, G. (2010). Meritocracy, modernization and students' occupational expectations: Cross-national evidence. *Research in Social Stratification and Mobility*, 28(3), 275–289. <https://doi.org/10.1016/j.rssm.2010.06.002>
- Marsh, H. W., Lüdtke, O., Trautwein, U., & Morin, A. J. S. (2009). Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. *Structural Equation Modeling: A Multidisciplinary Journal*, 16(2), 191–225. <https://doi.org/10.1080/10705510902751010>
- McDaniel, A. (2010). Cross-National gender gaps in educational expectations: The influence of national-level gender ideology and educational systems. *Comparative Education Review*, 54(1), 27–50. <https://doi.org/10.1086/648060>
- Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal*, 14(4), 535–569. <http://dx.doi.org/10.1080/10705510701575396>
- Organisation for Economic Co-Operation Development. (2019). *PISA 2018 results (volume II): Where all students can succeed*. OECD. <https://doi.org/10.1787/b5fd1b8f-en>
- Organisation for Economic Co-Operation Development. (2020a). *PISA 2018 Database* [Data set]. OECD. <http://www.oecd.org/pisa/data/2018database/>
- Organisation for Economic Co-Operation Development. (2020b). *Scaling procedures and construct validation of context questionnaire data*. OECD. http://www.oecd.org/pisa/data/pisa2018technicalreport/PISA2018_Technical-Report-Chapter-16-Background-Questionnaires.pdf
- Roderick, M., Coca, V., & Nagaoka, J. (2011). Potholes on the road to college: High school effects in shaping urban students' participation in college application, four-year college enrollment, and college match. *Sociology of Education*, 84(3), 178–211. <https://doi.org/10.1177/0038040711411280>
- Rowan-Kenyon, H. T., Perna, L. W., & Swan, A. K. (2011). Structuring opportunity: The role of school context in shaping high school students' occupational aspirations. *The Career Development Quarterly*, 59(4), 330–344. <https://doi.org/10.1002/j.2161-0045.2011.tb00073.x>
- Schmitt-Wilson, S., & Faas, C. (2016). Alignment of educational and occupational expectations influences on young adult educational attainment, income, and underemployment: Aligned expectations. *Social Science Quarterly*, 97(5), 1174–1188. <https://doi.org/10.1111/ssqu.12244>
- Schoon, I., & Parsons, S. (2002). Teenage aspirations for future careers and occupational outcomes. *Journal of Vocational Behavior*, 60(2), 262–288. <https://doi.org/10.1006/jvbe.2001.1867>
- Sikora, J. (2018). Aimless or flexible? Does uncertainty in adolescent occupational expectations matter in young adulthood? *Australian Journal of Education*, 62(2), 154–168. <https://doi.org/10.1177/0004944118776463>
- Sikora, J., & Pokropek, A. (2012). Gender segregation of adolescent science career plans in 50 countries. *Science Education*, 96(2), 234–264. <https://doi.org/10.1002/sce.20479>
- Sikora, J., & Saha, L. J. (2009). Gender and professional career plans of high school students in comparative perspective. *Educational Research and Evaluation: An International Journal on Theory and Practice*, 15(4), 385–403. <http://dx.doi.org/10.1080/13803610903087060>
- Silva, B. C., Bosancianu, C. M., & Littvay, L. (2020). *Multilevel structural equation modeling*. Sage.
- Tai, R. H., Qi Liu, C., Maltese, A. V., & Fan, X. (2006). Career choice. Planning early for careers in science. *Science*, 312(5777), 1143–1144. <https://doi.org/10.1126/science.1128690>
- Tsukahara, I. (2007). The effect of family background on occupational choice. *LABOUR*, 21(4-5), 871–890. <http://dx.doi.org/10.1111/j.1467-9914.2007.00395.x>
- Vermunt, J. K. (2003). Multilevel latent class models. *Sociological Methodology*, 33(1), 213–239. <https://doi.org/10.1111/j.0081-1750.2003.t01-1-00131.x>
- Wicht, A. (2016). Occupational aspirations and ethnic school segregation: Social contagion effects among native German and immigrant youths. *Journal of Ethnic and Migration Studies*, 42(11), 1825–1845. <https://doi.org/10.1080/1369183X.2016.1149455>



Wicht, A., & Ludwig-Mayerhofer, W. (2014). The impact of neighborhoods and schools on young people's occupational aspirations. *Journal of Vocational Behavior*, 85(3), 298–308. <https://doi.org/10.1016/j.jvb.2014.08.006>

Received: July 16, 2022

Revised: August 22, 2022

Accepted: October 02, 2022

Cite as: Jiang, T., Chen, J.-G., Xu, P.-C., & Zeng, P.-F. (2022). Multilevel latent profile analysis of Estonian secondary school students' career expectations with science achievement and gender as covariates. *Journal of Baltic Science Education*, 21(5), 788-800. <https://doi.org/10.33225/jbse/22.21.788>

Tao Jiang
(Corresponding author)

PhD, Professor, Department of Physics, School of Materials Science and Engineering, Taizhou University, 1139 Shifu Avenue, Jiaojiang District, Taizhou 318000, Zhejiang Province, China.
E-mail: hopejt@163.com
ORCID: <https://orcid.org/0000-0001-8330-3995>

Ji-gen Chen

PhD, Professor, Department of Materials Engineering, School of Materials Science and Engineering, Taizhou University, Taizhou 318000, Zhejiang Province, China.
E-mail: kiddchen@126.com
ORCID: <https://orcid.org/0000-0001-7580-3869>

Ping-chuan Xu

M.S., Professor, School of Physics and Astronomy, China West Normal University, Nanchong 637009, China.
E-mail: pcxu@163.com
ORCID: <https://orcid.org/0000-0001-7462-4965>

Ping-fei Zeng

PhD, Professor, College of the Teacher Education, Zhejiang Normal University, 688 Yingbin Road, Jinhua 321004, Zhejiang Province, China
E-mail: zpf@zjnu.cn
ORCID: <https://orcid.org/0000-0002-6069-1638>

