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Academic Resilience and Interrelationships to Special Education Needs of Students in Fourth Grade

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Abstract

In common understanding, resilience enables students to withstand adverse conditions. Resilient students achieve moderate to good educational outcomes in spite of high risks. To foster academic resilience, a deep understanding of risk and resources, their interplay and moderating effects is essential. We aim to achieve this goal by using hidden (latent) Markov modelling (HMM) to (1) identify risk and resilience in the Progress in International Reading Literacy Study (PIRLS) sample for Germany 2016 and (2) reflect on the interdependences between these factors. Furthermore, special educational needs (SEN) are introduced as a variable for post hoc analysis. A four-class solution was established and factors favoring resilience could be identified. Post hoc analyses of class allocations show that students with SEN are less likely being allocated to classes with high socio-economic resources and above average academic achievements than students without SEN.

Keywords

Academic resilience, special educational needs, PIRLS 2016 data for Germany, hidden (latent) Markov modelling

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Resiliencia Académica e Interrelaciones con las Necesidades Educativas Especiales de los Alumnos de Cuarto Curso

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Resumen

Según la literatura existente, la resiliencia permite a los alumnos enfrentarse y superarse en condiciones adversas. Los estudiantes resilientes logran resultados educativos moderados y buenos a pesar de los altos riesgos. Para fomentar la resiliencia académica es esencial comprender en profundidad el riesgo y los recursos, su interacción y sus efectos moderadores. Pretendemos alcanzar este objetivo mediante el uso de modelos de Markov ocultos (latentes) (HMM) para (1) identificar el riesgo y la resiliencia en la muestra del Progress in International Reading Literacy Study (PIRLS) de Alemania 2016 y (2) reflexionar sobre las interdependencias entre estos factores. Además, se introducen las necesidades educativas especiales (NEE) como variable para el análisis post hoc. Se estableció una solución de cuatro clases y se pudieron identificar los factores que favorecen la resiliencia. Los análisis post hoc de la asignación de clases muestran que los alumnos con NEE tienen menos probabilidades de ser asignados a clases con muchos recursos y un rendimiento académico superior a la media que los alumnos sin NEE.

Palabras clave

Resiliencia académica, necesidades educativas especiales, datos PIRLS 2016 para Alemania, modelos de Markov ocultos (latentes)

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There are numerous factors on different levels influencing academic success. While intelligence and (to a degree) grit are generally known as helpful resources (Ang et al., 2022; Zisman & Ganzach, 2021), Broer et al. (2019) showed the negative impact of low socio-economic resources on students' chances to achieve good educational outcomes.
Resilience can be seen as a moderating influence helping students to overcome adverse conditions (Butler et al., 2018; Fleming et al., 2020; Hollingsworth, 2019; Katz et al., 2020). Facilitating resilience and thus enabling the individual to cope/ bounce back successfully when faced with adversity or risks can be a significant step on the way to fair and inclusive education (Vitalaki et al., 2018). Understanding how resilience works and which factors have the most impact on academic outcomes as well as child development at large is therefore crucial.
To operationalize resilience for the current study we refer to Hochschild and Schäfer (2018), who defined those students as resilient who achieved moderate to good academic outcomes in spite of low socio-economic resources (Hochschild & Schäfer, 2018). Low socio-economic status (SES) is a very commonly addressed risk in the context of (academic) resilience (Masten, 2007; 2015).

Disabilities have also been addressed as risks or at least as averse conditions to overcome (Butler et al., 2018). Special educational needs (SEN) on the other hand are not always associated with a (physical) disability. Furthermore, the most common SEN in Germany (difficulties in learning and social and emotional development) are overly prevalent in families with low socio-economic resources (Goldan & Kemper, 2019). It is therefore unclear if SEN and low socio-economic resources have to be treated as confounding conditions or separate risks. We decided to include SEN in post hoc analysis to evaluate if the mechanisms of risk and resilience apply similar for both population (with and without SEN).

The Current Study

We use hidden (latent) Markov modelling (HMM; Visser & Speekenbrink, 2010), an approach similar to latent class analyses (LCA; Vermunt, 2010; Vermunt et al., 1999) on the Progress in International Reading Literacy Study (PIRLS) 2016 data for Germany (Hußmann, Wendt, Bos, Bremerich-Vos, et al., 2020) to identify patterns of risk and resilience in fourth-grade students for an exemplary European country. We aim to (1) establish a suitable multi-class solution with at least one resilient class, (2) compare class allocation between students with and without SEN and (3) compare class allocation between different kinds of SEN.

Research is led by three questions and subsequent hypotheses below:

- Can we identify resilient students using an HMM approach on PIRLS 2016 data for Germany?
- Can class allocation be predicted by SEN?
- Are there differences in class allocation between different kinds of SEN?

Earlier studies using LCA to analyze resilience in a different context identified a three-class solution as most suitable (Anthony & Robbins, 2013). Therefore, referring to the first question, we predict a three-class model. Based on the theoretical background we expect one class with

high resources (low risks) and high academic achievements, a second resilient class with high risk (low socio-economic resources and moderate to high achievements), and a third class with low socio-economic resources (high risk) and low achievements. As a fourth class a cluster with high socio-economic resources (low risk) and low to moderate achievements is possible. We predict that the majority of students with SEN will be allocated to classes with low socio-economic resources (high risk) due to the increased prevalence of special needs and disabilities in families with lower SES (Goldan & Kemper, 2019; Lenkeit et al., 2022). In the following, we will present the theoretical background for our analysis. This comprises of definitions of academic success and resilience as well as a brief introduction into resilience research in students with SEN. Furthermore, we address studies concerning resilience in large-scale educational data and using latent class modelling.

Academic Success and Resilience

Under academic success, we summarize educational achievements like degrees and trajectories. Therefore, successful students would achieve good grades and (are expected to) enter pathways to higher education.

Factors that influence students' academic success can be organized at three levels. First, there is the student. Their traits contain factors like intelligence (Masten, 2007), personality (Mavroveli & Sánchez-Ruiz, 2011), psychological capital (Freyberg, 2011), self-concept (Çetinkaya, 2017) and mindset (Carvalho & Skipper, 2020). The second level consists of factors within the students` social environment. This includes the relationships and communication with friends, family and with other caring adults (Masten, 2007; Opp et al., 2020; Touloupis, 2021), as well as the socio-economic status and resources of the family and therefore the student (Broer et al., 2019; Hochschild & Schäfer, 2018). Finally, there are factors within schools and the educational system influencing students' success. Within this level, relationships and interactions with teachers and peers, the perceived level of requirement and the quality of education are relevant factors (Hochschild & Schäfer, 2018). All those factors are interrelated and can have different impact on education and trajectory of students.

Research on academic resilience focuses on students who are unexpectedly successful, this means achieving average to high academic outcomes in spite of high educational risks. We try to identify those protectors in the brought set of correlates that help mediate or moderate adverse conditions (Masten, 2015).

There are other forms of resilience beside academic resilience. Psychological resilience for example enables individuals to withstand traumatic events without developing post-traumatic stress disorder (Connor & Davidson, 2003). Physical resilience is the ability to withstand diseases and recover from physical stress (Whitson et al., 2018). All these forms of resilience emphasize different factors and are concerned with different populations.

Risk and resilience have been deemed most impactful in educational transitions (e.g. primary to secondary school; Caleon et al., 2017; Cappella & Weinstein, 2001). We took this into account and focused on academic resilience in fourth-grade students.

Resilience and SEN

Students with SEN often face additional risks compared to students without SEN (Freyberg, 2011). In a representative sample of Portuguese students (N= 1181) Gaspar et al. (2016) showed that students with SEN have lower resilience then their peers without SEN. At the same time the authors underline the importance of personal and social resources for health related quality of life, wellbeing and academic achievement (Gaspar et al., 2016). The results presented indicate that optimism, resilience, self-esteem and social support satisfaction can mediate the influence of SEN status on subjective wellbeing and academic performance (Gaspar et al., 2016). These findings underline the importance of resilience in special education.

Viewed from an international perspective, numerous studies have focused on resilience in students with specific types of SEN (e.g., Butler et al., 2018; Gilmore et al., 2013; Skrzypiec et al., 2016). However, this is not the case in Germany. While resilience has emerged as a popular area of research (Freyberg, 2011), only a limited number of studies have specifically addressed SEN (e.g., Gebhardt, 2009).

Resilience in large-scale educational data

Although resilience research within the context of special education in Germany remains relatively rare, earlier studies have addressed resilience in the education of students without SEN (Freyberg, 2011). This paper will closely analyze one of these studies due to its relevance and similarities to the current research.

In a special evaluation of the Program for International Student Assessment (PISA) 2015 resilience was addressed. Low SES was seen as the most impactful risk , a positive school climate as the most meaningful asset (Hochschild & Schäfer, 2018). In addition to this, some risks within the student's home and social environment were pointed out. If the language spoken at home differs from the language spoken in school (German) the chance of being resilient is cut in half. In addition, female students are slightly less likely to be resilient than males (Hochschild & Schäfer, 2018). Resources were seen from a school organizational point of view and individual or social assets other than SEN were not represented (Hochschild & Schäfer, 2018).

Students who achieve adequate educational results (at least level 1; OECD, 2014) in spite of low SES are considered resilient (Hochschild & Schäfer, 2018). In this framework (1) the percentage of resilient students among all students with low SES was compared internationally and (2) the national increase of resilience in Germany was contrasted with developments in other OECD nations (Hochschild & Schäfer, 2018). With 32.3% resilient students in 2015, Germany is above the OECD average of 25.0%. The increase of 7.1% from 2006 to 2015 indicates a positive development.

Modelling resilience via LCA

Anthony and Robbins (2013) used LCA to model resilience to substance abuse and delinquency of 6th to 8th-grade students from public housing neighborhoods in Arizona (United States of

America). They established a three-class model (Anthony & Robbins, 2013), underlining the suitability of the analytical approach for resilience research.

In summary, resilience has been successfully evaluated in special education (Fleming et al., 2020; Gaspar et al., 2016; Gebhardt, 2009), large-scale educational data (Hochschild & Schäfer, 2018), and using LCA (Anthony & Robbins, 2013). In our study large-scale educational data (PIRLS 2016 for Germany Hußmann, Wendt, Bos, Bremerich-Vos, et al., 2020) is analyzed using HMM (Visser & Speekenbrink, 2010). In an additional step, the interplay between resilience and SEN is reviewed.

Method

PIRLS 2016 data for Germany

The excerpt of PIRLS 2016 data for Germany used in this analysis consists of 161 variables within N=3959 observations. This is a nationally representative sample of schools and students (LaRoche et al., 2017).

Some items were summarized according to the underlying theoretical framework. The language spoken at home was reduced to a factor with three levels “not German (0)”, “German (1)” and “German plus additional languages (2)”. The language spoken in school for the sample will be German. If the language spoken at home is not German, the chance of being resilient is expected to be greatly reduced (Hochschild & Schäfer, 2018). Some other reductions were made to limit the number of indicators. The resource generator (Hußmann, Wendt, Bos, & Rieser, 2020; van der Gaag & Snijders, 2005) and the number of wealth assets (Hußmann, Wendt, Bos, & Rieser, 2020) were aggregated to single variables. For reading proficiency, the first of five plausible values provided in PIRLS 2016 (Hußmann, Wendt, Bos, Bremerich-Vos, et al., 2020) was used. Therefore, 92 variables remained. Scale composition, item description and item statistics are included in the appendices.

Missing data was handled using multiple imputations via chained equations (MICE) in a R (R Core Team, 2023) package (van Buuren & Groothuis-Oudshoorn, 2011). $m = 20$ Imputations were carried out.

While analysis was carried out using the individual items, these items were aggregated to scales for descriptive evaluation (see Figure 2; Appendix A). Socio-economic status summarizes all variables concerned with the financial and educational background as well as the migration status and family constellation. Academic self-concept, personality and parental supervision represent preexisting scales in PIRLS data (Hußmann, Wendt, Bos, Bremerich-Vos, et al., 2020; Hußmann, Wendt, Bos, & Rieser, 2020). Self-concept and parental supervision are rated by the students and personality is rated by the parents (Hußmann, Wendt, Bos, & Rieser, 2020). The perceived requirement level at school, the perceived support received from teachers and mobbing are self-assessment scales. School climate is rated by the schools´ principal (Hußmann, Wendt, Bos, & Rieser, 2020). The academic outcomes summarize all reading ability scores, grades in math and German as well as some predictions

of parents and teachers about the educational career of the students/ their children. All scale means reported are standardized (z-scale).

We can identify a total of 211 students with SEN. Of those, 66 are diagnosed with learning difficulties (31.3%), 37 with social and emotional development needs (17.5%), 15 with visual, auditive, or physical disabilities (7.1%), 31 with speech impairments (14.7%), 54 have multiple combined needs or disabilities (25.6%) and 8 have undefined or other SEN (3.8%).

Modeling Approach

To address the matter of hidden but similar classes within cases methods like cluster (e.g. k-means or hierarchical), latent class or latent profile analysis can be used (Bacher, 2002). However, many of the applications do either not include latent variables and probabilistic theory or do not allow for indicators with mixed types of variables.

HMM can uncover unknown latent structures. Though mainly used for longitudinal settings, they can also be applied in cross-sectional analysis. This way they address measurement errors, detect unobservable states and compress information across different types of observations (e.g. Fink, 2003).

We used depmixS4 (Visser & Speekenbrink, 2010) and calculated solutions with two to six classes. We expected three classes as they were found by Anthony and Robbins (2013), but also took a simpler model (2 Classes) and more complex models (4 to 6 classes) into consideration. Models with more than six classes or less than two were deemed unplausible or not informative with resilience as theoretical background in mind.

We performed the Kruskal-Wallis-Test or if applicable χ^2-Tests and calculated effects on class allocation for every variable. Due to the large sample size, all variables achieved statistical significance ($p < 0.01$). We excluded 10 variables due to their very small effect ($\eta^2 < 0.001$ for Kruskal-Wallis-Test or $V < 0.2$ for χ^2-Tests). 82 variables remained. All models were calculated again and suitability of the chosen solution was reinsured for the new excerpt.

To evaluate the relationship between the latent classes and the external variables an approach with three steps was chosen (Bakk & Kuha, 2021). A measurement model was estimated. Students were assigned to the most probable latent classes. Then the correspondences were assessed post hoc. Therefore, we used a classical three-step. For post hoc analysis, Fisher´s Exact Test was used to evaluate the interrelationship between SEN and class allocation. Information about SEN was taken from the teacher tracking form (Hußmann, Wendt, Bos, & Rieser, 2020).

To evaluate possible variations between different kinds of SEN, subgroups were constructed to preserve viable cell sizes. We summarized visual, physical/motorial and hearing disabilities to one group and all combinations of different SEN to another subgroup.

Entropy and latent class posterior probability for the selected solution indicate very small differences between crisp class states and class probability. Therefore, crisp states were used for post hoc testing.

Transparency and Openness

The complete PIRLS 2016 sample for Germany and within all data used for analysis is available for scientific use (Hußmann et al., 2020). Data was analyzed using R, version 4. 3.1 (R Core Team, 2023) and the packages, mice version 3.16.0 (van Buuren & Groothuis-Oudshoorn, 2011), depmixS4 version 1.5.0 (Visser & Speekenbrink, 2010) and psych version 2.4.1 (Revelle, 2023). For a table of all used scales, see Appendix A and for descriptive item statistics see Appendix B. Analysis code for this study is available by contacting the corresponding author. This study's design and its analysis were not pre-registered. All necessary approvals in accordance with local law were obtained for the initial PIRLS 2016 inquiry (e.g. Land Brandenburg, 2016). Approvals must be obtained for each region, and not all regions provide a comprehensive overview of granted permissions. The secondary data analysis conducted in this study does not require additional approval.

Findings

Model Selection

The model best suitable was chosen based on contextual plausibility, Bayesian Information Criterion (BIC), entropy, average latent class posterior probability (ALCPP) and Akaike Information Criterion (AIC; Rost, 2004; Weller et al., 2020). A four-class solution was selected. Rubins rule is not applicable in this scenario. To control for bias resulting from imputations, calculations were conducted in the first and five randomly drawn imputations. All six imputations are represented in Figure 1.

Based on BIC alone a three-, four- and five-class solution would be adequate (see Figure 1). The three-class solution was rejected based on entropy (see Figure 1). Following the principle of parsimony (e.g. Grün & Leisch, 2008), we selected the less complex of the two remaining options and chose the four- over the five-class model.

Figure 1

Model fit Comparison

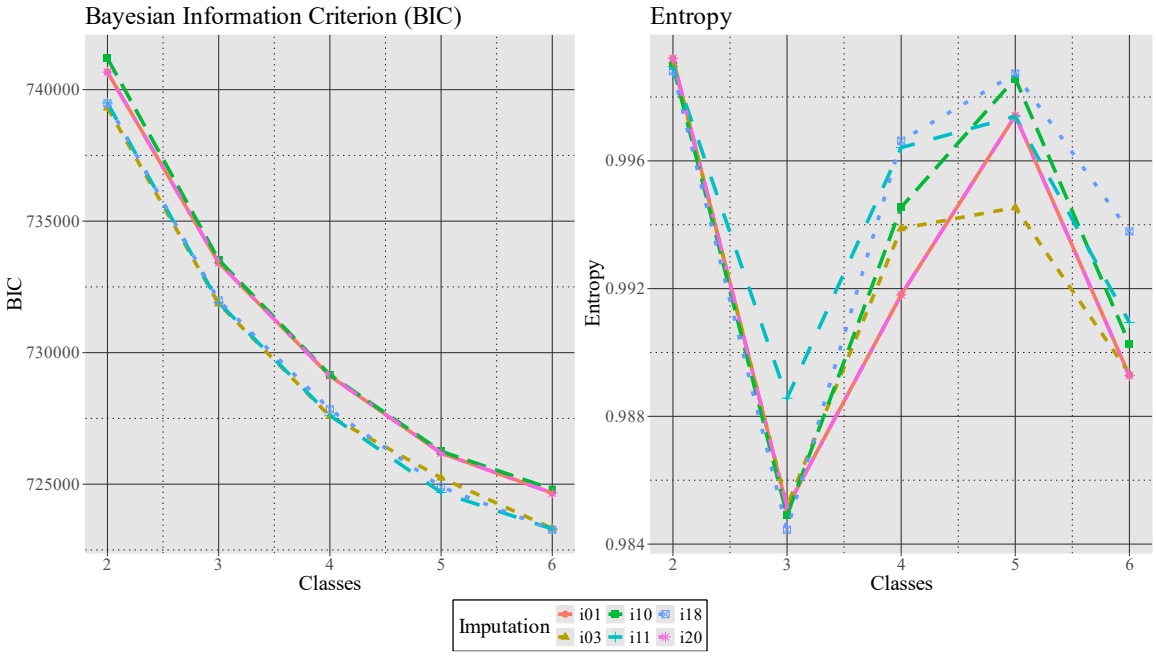

Table 1

Model Indicators

Indicator	2 Classes	3 Classes	4 Classes	5 Classes	6 Classes
AIC	737759	729051	723292	718899	715921
BIC	740668	733418	729117	726182	724661
Entropy	1.00	0.99	0.99	1.00	0.99
ALCPP	0.99	0.97	0.96	0.95	0.95
Min cell size	1914.00	1011.00	849.00	663.00	510.00
BLRT (p-value)	0.000	0.000	0.000	0.000	0.000

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion
ALCPP = average latent class posterior probability; BLRT = Bootstrapped likelihood ratio test

Patterns of Risk and Resilience in the Four Class Solution

In the chosen solution (Figure 2), class 1 (n=1230) has high socio-economic resources (low risks) and high achievements. The second class (Class 2; n=920) achieves moderate educational results in spite of low socio-economic resources (high risks). Following the classification by Hochschild and Schäfer (2018) this class will be considered resilient. Class 3 (n=880) has relatively high socio-economic resources but only moderate achievements. Class 4 (n=929) has low socio-economic resources (high risks) and low educational achievements.

Figure 1

Standardized Scale Means

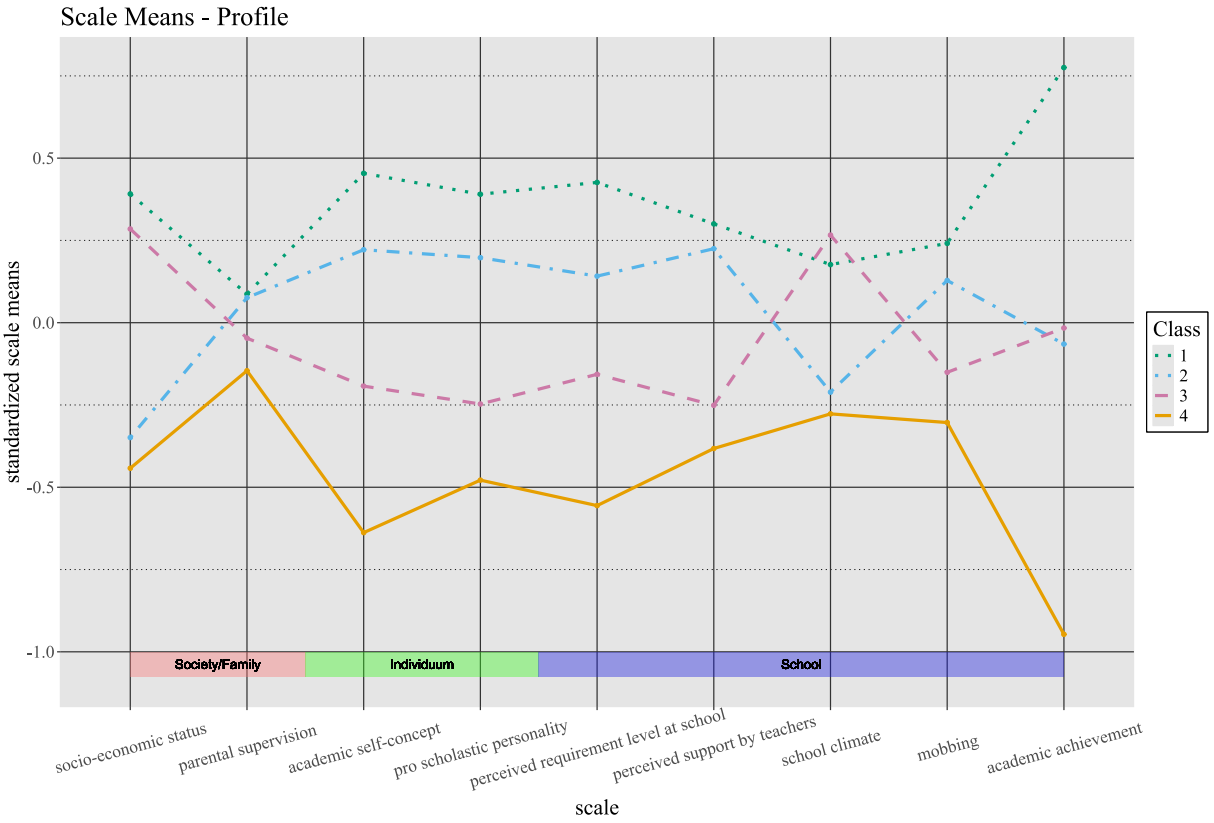

Table 2

Partial η^2 of Scales

Scale	η^2	p-value
socio-economic status	0.40	<0.01**
parental supervision	0.02	<0.01**
academic self-concept	0.50	<0.01**
pro scholastic personality	0.44	<0.01**
perceived requirement level at school	0.13	<0.01**
perceived support by teachers	0.07	<0.01**
school climate	0.004	<0.01**
mobbing	0.03	<0.01**
academic achievement	0.30	<0.01**

Note. $^{*}p < .05$; $^{**}p < .01$.

Figure 2 shows the standardized means of the included scales. All scales have a significant overall influence on class allocation (Table 2). Besides SES and educational achievement, academic self-concept, a pro-scholastic personality and the perceived requirement level at school have a high impact on class allocation. School climate and parental supervision have the lowest effect overall.

Regarding gender, the sample consists of 49% boys (51% girls). Class 1 (high socio-economic resources high achievements) has 57% boys, while class 2 (resilient class) has 35%.

Class 3 (high socio-economic resources and moderate achievements) consists of 36% and class 4 (low socio-economic resources and low achievements) of 41% boys.

Figure 3

Class Allocation by SEN-status

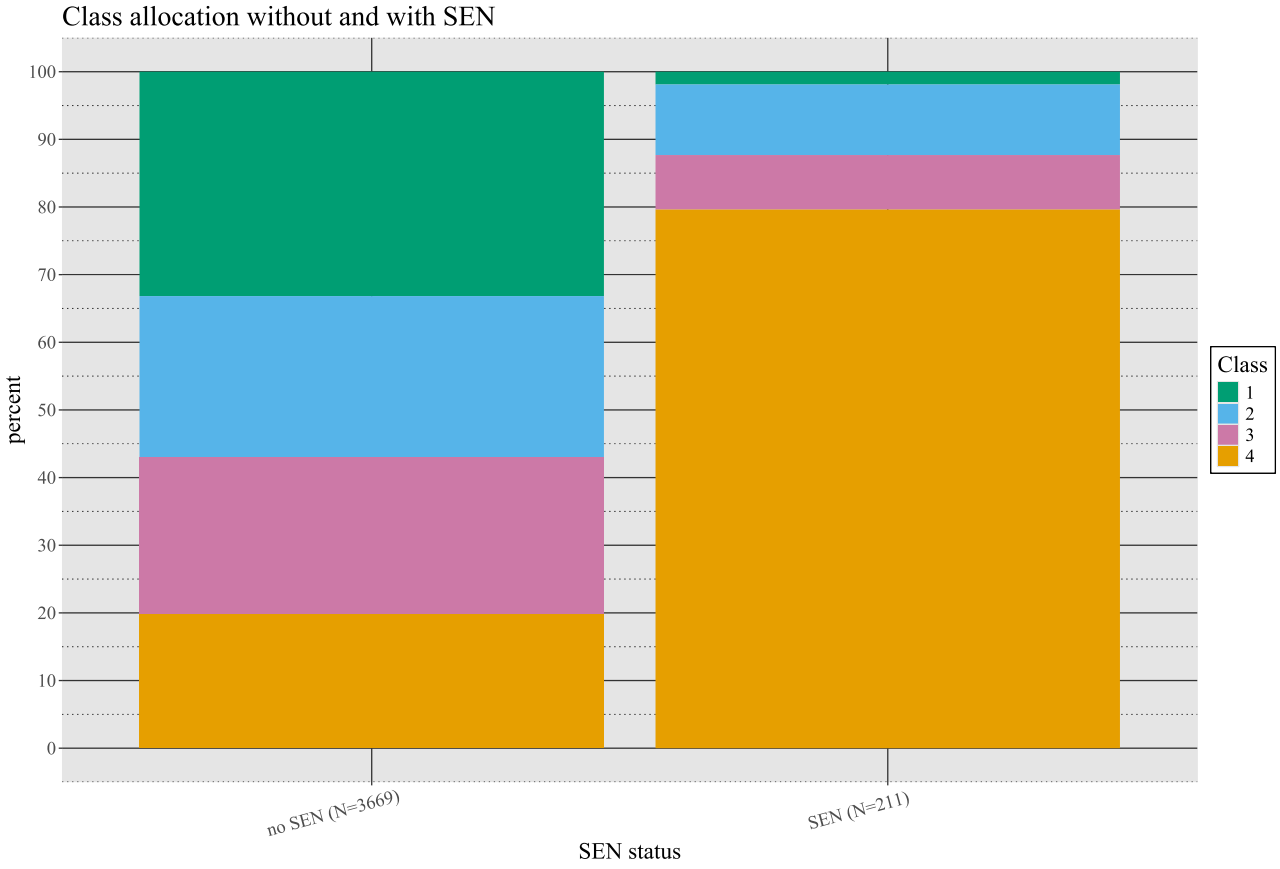

Figure 3 shows class allocation for students without SEN and students with SEN in percent. On a descriptive level, students with SEN are most likely (79.6%) to be in the fourth class (low socio-economic resources and low achievements). 10.4% are in the resilient second class (low socio-economic resources and moderate achievements) and 8.1% are in class 3 (high socio-economic resources and moderate achievements). In class 1 (high socio-economic resources and high achievements) are only 4 of 211 students with SEN (1.9%). The differences in class allocation, tested with Fisher´s Exact Test, were significant ($p < 0.01$).

Table 3 shows the relative probability of class allocation for students with SEN. The individual cells represent the probability of being allocated to a class (columns) rather than one of the other classes (rows).

The probability is calculated from odds ratio (*OR*) and can be interpreted as a measure of effect for χ^2-tests. A strong tendency to the fourth class (low socio-economic resources and low achievements) over every other class can be seen.

Overall, classes with less favorable SES (class 2 and 4) are prevailing for students with SEN. Classes with moderate to high outcomes (class 1, 2, and 3) are less prevalent in the SEN

population. Due to the small cell size for class 1 and SEN condition (n=4), the reported probabilities in the first row and column should be interpreted with some caution.

In simplified models comparing (1) classes with high versus low socio-economic resources (class 1 and 3 versus 2 and 4) and (2) classes with moderate to high versus low achievements (class 1, 2 and 3 versus 4) the results correspond to the more detailed test (Table 3). There is a strong and significant tendency for students with SEN to be in classes with lower SES (class 2 and 4; $OR = 11.69$; $p < 0.01$) and low achievements (class 4; $OR = 15.87$; $p < 0.01$). Overall, 54.8% of students without SEN are achieving moderate to high educational results despite low SES. For students with SEN, this is only true for 11.6%.

A comparison within subgroups of the SEN population indicates additional differences in class allocation. An association between subgroup and class allocation over all subgroups and classes is significant using Fisher's exact test ($p < 0.01$). Figure 4 shows the SEN subgroups and respective class allocations. The first class (high socio-economic resources and high achievement) is only represented in three out of six subgroups. Class 2 (resilient class) is represented in all groups. The second biggest class is class 3 (high socio-economic resources and moderate outcomes). Class 3 is especially prevalent among students with social and emotional needs or physical/sensory disabilities.

Table 3

Probability of class allocation for students with SEN

… rather than class	Probability of being allocated to class…			
Class	1	2	3	4
1		0.88	0.86	0.98
2	0.12		0.44	0.88
3	0.14	0.56		0.91
4	0.02	0.12	0.09	

Figure 2

Class allocation by SEN subgroups

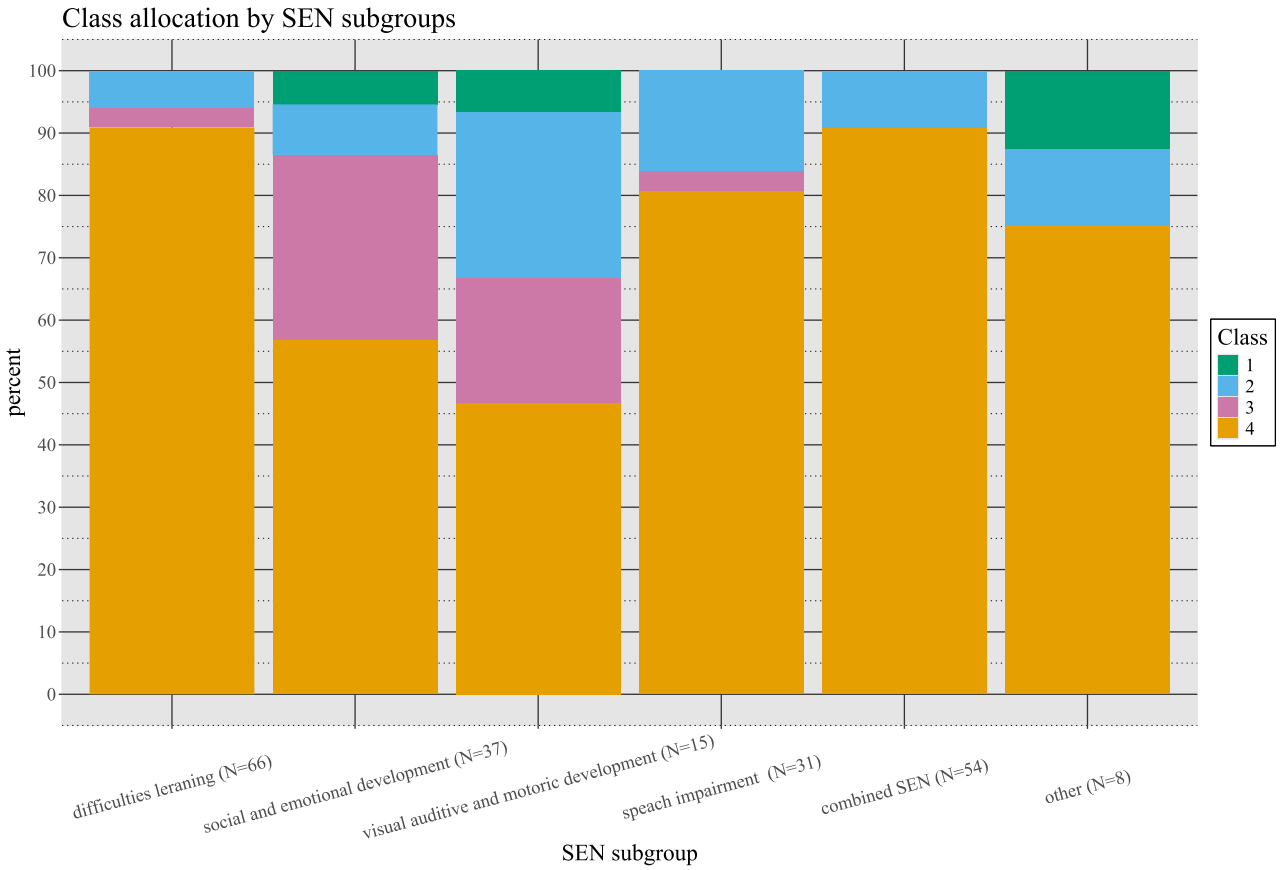

Table 4

High versus low SES by SEN subgroup

SEN subgroup	Favorable SES	Low SES
learning difficulties (N=66)	3.0%	97.0%
social and emotional development (N=37)	35.1%	64.9%
visual auditive and motoric development (N=15)	26.7%	73.3%
speech impairment (N=31)	3.2%	96.8%
combined SEN (N=54)	0.0%	100.0%
other (N=8)	12.5%	87.5%

Tables 4 and 5 display the odds of being in a class with high socio-economic resources (Table 4) or high academic achievement (Table 5) depending on specific SEN. For the socio-economic background of the SEN subgroups (Table 4) low socio-economic resources are dominant in all sub-groups. It must be emphasized at this point, that not a single student with multiple combined SEN (n=54) is allocated to a class with favorable SES (class 1 and 3). All 9.3% of these students achieving moderate to good educational results do so being in the resilient class (class 2).

Table 5
High versus Low Academic Achievements by SEN Subgroup

SEN subgroup	Moderate to high achievement	Low achievement
learning difficulties (N=66)	9.1%	90.9%
social and emotional development (N=37)	43.2%	56.8%
visual auditive and motoric development (N=15)	53.3%	46.7%
speech impairment (N=31)	19.4%	80.6%
combined SEN (N=54)	9.3%	90.7%
other (N=8)	25.0%	75.0%

A similar picture can be seen for the academic achievements. It is becoming apparent that students with learning difficulties and students with combined SEN have the overall lowest odds for moderate or high achievements. Students with sensory or motorial disabilities and students with special social and emotional needs have the highest odds of favorable educational results.

Discussion

A Model of Resilience

We were able to identify patterns of academic resilience in fourth-grade students in Germany using an HMM approach on PIRLS data 2016. However, resilience in our model does not lead to high academic achievements. Resilience might be "ordinary magic" (Masten, 2015, p. 1), but the academic achievements of resilient students in our model are only moderate and far lower than those of students with higher socio-economic resources. This is still a major improvement over non-resilient students, but resilience is not negating all risks students might face. Nevertheless, moderate to good educational results in spite of sub-ideal conditions and socio-economic resources are possible.

In our model, about 49.8% of students with low SES can be considered resilient. Compared to the 32.2% found in PISA 2015 (Hochschild & Schäfer, 2018) that is an additional 17.6%. This difference could have multiple reasons. First, PIRLS targets primary school students while PISA targets secondary school students. The percentage of resilient students might change over time. Secondly, academic achievement is defined differently in both studies. While PISA evaluates a broad spectrum of educational professions, PIRLS is mainly focused on reading skills. Finally, it remains unclear how Hochschild and Schäfer (2018) define and measure the overall SES.

The chosen approach allows us to analyze protective and fostering factors as well as risk factors and their interplay. It is revealed that self-concept and pro-scholastic personality (traits) in combination with the perception of the requirement level at school and support through teachers can moderate socio-economic risks. This is true for classes 2 and 3 in our model. Class 2 (resilient class) shows high risks but moderate academic achievements. This could be attributed to the named protective factors. Class 3 (high socio-economic resources and

moderate achievements) on the other hand has high resources on a socio-economic level. The achieved educational results for this class are only moderate though. This could be attributed to low self-concept and personality scores as well as an unpropitious perception of requirements and support by teachers.

As shown in other studies (Anthony & Robbins, 2013; Cappella & Weinstein, 2001) parental supervision has only a small influence on resilience and in our case class allocation. The scale used to assess parental supervision in PIRS 2016 mostly asks for the quantity of time a parent or both parents spend at home (Hußmann, Wendt, Bos, & Rieser, 2020). This does not assess the quality of parenting, or the support received from parents. These, however, might be more relevant factors in facilitating and fostering resilience (Anthony & Robbins, 2013; Opp et al., 2020).

School climate was expected to be highly relevant for building resilience (Hochschild & Schäfer, 2018). This could not be confirmed in the current study. A possible explanation for this result is that the school climate in PIRLS is rated by the schools´ principals (Hußmann, Wendt, Bos, & Rieser, 2020). Therefore, it might be more an approximation of the schools´ socio-economic environment than the social atmosphere at school. This is supported by the fact that classes with higher SES (class 1 and 3) show better school climate. Also, there is no association between mobbing (rated by students) and school climate (rated by the principals) in our model (Figure 2).

Interrelationships with SEN

Addressing resilience based on the reported findings, the situation of primary school students with SEN is unfavorable at best. Students with SEN are significantly more likely to be allocated to classes with low educational outcomes than students without SEN. Seeing SEN itself as a (determining) risk factor (Gilmore et al., 2013) might be misleading though. The overwhelming majority (90.0%) of students with SEN have low socio-economic resources. Therefore, these children face multiple risks. It has been shown that the accumulation of multiple risk factors has much higher effect on resilience than the severity of a single risk (Opp et al., 2020). Teachers schooling students with SEN must be prepared to face a population with a multitude of risk factors and little to no protectors. This emphasizes the need to improve students' self-concept by facilitating and fostering a positive style of attribution (Müller-Luhnau, 2015). Also, good and sensitive adaptation of materials and requirements can play an important role (Hochschild & Schäfer, 2018; Roos & Grünke, 2011). Good teacher-student relations and supportive teaching can further help foster resilience (Hochschild & Schäfer, 2018; Masten, 2015). Thus the socio-economic resources of students have to be considered unmodifiable by the educational system (Müller-Luhnau, 2015; Roos & Grünke, 2011), which is not the case for other significant factors. The current study has shown that students with SEN can be resilient and achieve at least moderate academic outcomes in spite of multiple risks.

SEN Subgrupos

Everything said for children with SEN at large is also true for the different subgroups analyzed in this study. Nevertheless, there are still significant differences within the SEN population. Thus, resilient students can be found in all subgroups, the same is not true for favorable socio-economic resources. Not one student with multiple or combined special needs is allocated to a class with high socio-economic resources (class 1 and 3). At this point, a strong correlation between low SES and SEN can be postulated. In the SEN population, high SES is most prevalent in students with social and emotional needs. It can be argued that the relatively high percentage (29.3%) of these students found in class 3 (high socio-economic resources and moderate achievements) is a characteristic of this type of SEN. All variables moderating socio-economic influences depend on good self-regulation and interactions with the social environment. This might be especially challenging for students with social and emotional disorders.

Conclusion

In conclusion, we were able to establish a (latent) hidden Markov model in PIRS 2016 data for Germany. We identified one resilient class and analyzed the interplay of multiple factors. First, it should be said that many children are growing up under favorable conditions and achieving good academic results. Further, there is still a major impact of socio-economic resources on educational success in Germany. Though this effect can be moderated by other factors it cannot be completely negated. Even resilient students achieve much lower outcomes than students with higher SES.

Moderating factors like personality, academic self-concept, perception of requirements and support from teachers can be helpful, but they can be risk factors as well. Having low academic self-concept, personality (traits) leading to adverse interactive experiences, feeling overwhelmed by requirements at school or being left alone by teachers may resultin only moderate achievements in spite of relatively high SES.

For students with SEN, the overall situation is significantly worse. They tend to have low (socio economic) resources and are highly likely to have low academic achievements at the end of primary school. Nevertheless, a small percentage of resilient students with SEN show that even in the face of multiple adverse conditions academic success is possible. Knowing the average starting conditions of the SEN population underlines the importance of resilience especially for these students. Adverse conditions can be overcome and their negative effects can be greatly reduced by fostering resilience. All relevant moderators outlined in this study can be influenced by teachers and the educational systems.

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