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AN ANALYSİS OF THE ACADEMİC ACHİEVEMENT PROFİLES OF YEAR 8 STUDENTS USİNG LATENT PROFİLE ANALYSİS

ANÁLISE DOS PERFIS DE DESEMPENHO ACADÊMICO DE ALUNOS DO 8º ANO POR MEIO DA ANÁLISE DE PERFIS LATENTES

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Abstract
This study examined the academic performance patterns in core subject grades among 8th-grade students attending schools in the province of Antalya and assessed how these patterns varied according to different educational and sociocultural variables. Going beyond approaches that focus solely on average grades, latent profile analysis was used to determine whether students could be grouped into similar performance categories. The sample consisted of 314 students. Grades in Turkish, mathematics, science, social studies, foreign language, and religious culture were included in the model as continuous variables. Model comparisons revealed four distinct profiles, presenting a sequential academic model ranging from low to high performance; mathematics and foreign language courses provided clearer distinctions between the profiles. Ordinal logistic regression analysis was conducted to identify the variables explaining these profiles. The results indicate that academic performance profiles are related not only to cognitive performance but also to the educational and sociocultural resources available to students.

Keywords: Latent Profile Analysis. Ordinal Logistic Regression. Academic Achievement Profiles.

Resumo
Este estudo analisou os padrões de desempenho académico nas notas das disciplinas básicas dos alunos do 8.º ano que frequentam escolas na província de Antália e avaliou como esses padrões variam em função de diferentes variáveis educativas e socioculturais. Indo além das abordagens que se centram apenas nas notas médias, foi utilizada a análise de perfis latentes com o objetivo de determinar se os alunos poderiam ser agrupados em categorias de desempenho semelhantes. A amostra é composta por 314 alunos. As notas de turco, matemática, ciências, estudos sociais, língua estrangeira e cultura religiosa foram incluídas no modelo como variáveis contínuas. As comparações do modelo revelaram quatro perfis, apresentando um modelo académico ordenado que vai do baixo desempenho ao alto desempenho; as disciplinas de matemática e língua estrangeira proporcionaram distinções mais claras entre os perfis. Foi realizada uma análise de regressão logística ordenada para identificar as variáveis que explicam estes perfis. Os resultados mostram que os perfis de desempenho académico estão relacionados não só com o desempenho cognitivo, mas também com os recursos educativos e socioculturais a que os alunos têm acesso.

Palavras-chave: *Análise de Perfis Latentes. Regressão Logística Ordinal. Perfis de Desempenho Académico.*

1 INTRODUCTION

In the field of educational sciences and psychometrics, student achievement has traditionally been measured using average scores. This approach often emphasizes linear relationships between variables. However, individual achievement is shaped by numerous factors, such as cognitive abilities, affective traits, and environmental influences (Collins & Lanza, 2010; Hancock *et al*., 2019). The presence of students with diverse characteristics in the educational process can make it difficult for the same methods and techniques to be equally effective for all. Success-score-based assessments that ignore the existence of different profiles can cause various issues. Recently, different statistical modeling techniques have gained popularity to address this methodological limitation and explore diversity within subgroups of the population. Latent class analysis (LCA), which groups students based on similar characteristics, is one such method (Nylund-Gibson & Choi, 2018; Porcu & Giambona, 2017).

By distinguishing between homogeneous student groups and the diverse differences among them, variations in individual academic performance can be observed. Examining which subjects different profiles perform better or worse in allows for more targeted educational interventions (Fagginger Auer *et al*., 2016; McMullen *et al*., 2020). Identifying these latent classes is crucial for understanding the structural patterns underlying educational outcomes (Araújo *et al*., 2019; Özberk & Türk Kurtça, 2021). Although the formation of these profiles results from cognitive outcomes based on academic achievement, it is also important to consider affective and environmental factors (Lee *et al*., 2021). In-school and out-of-school dynamics, along with socio-cultural backgrounds and family-related environmental factors, significantly influence achievement group formation (Sideridis *et al*., 2021). Hattie (2009) emphasizes this in his study, which synthesizes hundreds of meta-analyses. A large portion of the variance in achievement levels arises from available resources and environmental factors. Physical learning environments and external support mechanisms directly impact this process.

Examples include the number of books at home (sociocultural capital), class size (physical conditions of the learning environment), and access to private tutoring (external academic activities). The influence of these factors on cognitive achievement is well-documented (Hattie, 2009). Additionally, improving these factors can help individuals reach higher achievement profiles. These predictors need to be empirically tested to identify at-risk disadvantaged groups, enabling the development of data-driven intervention programs (King *et al*., 2016; Lamont *et al*., 2017).

The main goal of this study is to analyze the academic performance patterns of Year 8 students in the center of Antalya. These patterns are based on in-term achievements in core subjects. Homogeneous profiles formed by the students will be identified using the LPA method. LPA is a profile-oriented approach that aims to find homogeneous groups within a population that cannot be directly seen, based on individuals' observed score patterns (Porcu & Giambona, 2017). In other words, it assumes that students within each latent profile share similar response probabilities or similar average score patterns (Haertel, 1984). The main purpose of this method in educational research is its ability to identify complex interactions and diverse achievement profiles among students' academic performance from a holistic perspective, unlike traditional variable-focused methods (Kim, 2023). In the analysis, scores from mathematics, Turkish, science, social studies, foreign language, and religious culture lessons were used as continuous indicator variables. The most appropriate class structure was tested based on students' performance in these subjects. An individual's assignment to a specific profile cannot be explained solely by cognitive ability. This process is influenced by the physical conditions of the educational environment and socio-cultural resources. The effects of variables believed to influence profile formation—such as class size, number of books at home, and status of private tutoring—will be examined. Class size reflects the dynamics of the educational environment, private tutoring indicates out-of-school academic support, and the number of books at home reflects the student's sociocultural background (Hattie, 2009). An ordered logistic regression analysis will be used to examine the effects of these independent variables.

By examining the variability in core subjects across the different achievement profiles identified through the research, a data-driven approach will be established for interventions and improvements in the teaching process. Furthermore, identifying at-risk student profiles is essential for planning targeted interventions, as it involves understanding each profile's unique academic needs and challenges. The research questions for the study are listed below:

1. How many distinct profiles are formed among student groups based on performance in core subjects?

2. How does performance in core subjects vary across different profiles?

3. What variables influence the formation of the profiles identified through LCA?

2 METHODS

2.1 Study group

The research sample includes 321 Year 8 students from schools in the center of Antalya province. Purposive sampling was employed as the sampling method. Purposive sampling is a technique where cases are intentionally selected to enable a detailed examination of situations rich in information relevant to the research goal (Patton, 2014). 37.7% of the students are male (n=121). Regarding mothers' educational levels, 56.7% have primary education, 30.2% have secondary education, and 13.1% have tertiary education. As for fathers' educational levels, 26.8% have primary education, 46.4% have secondary education, and 26.8% have tertiary education.

2.2 Data collection tools

As part of the research, mid-term exam scores in core subjects (Turkish, Mathematics, Science, Social Studies, Foreign Language, Religious Culture, and Ethics) were obtained from the relevant institutions following authorization. Additionally, data on gender, mother's educational attainment, and father's educational attainment were collected from participants using a demographic information form. Furthermore, variables related to individuals' educational conditions and resources—such as class size, whether they received private tutoring, and the number of books—were gathered.

2.3 Data collection process

Participants were not offered any financial or non-financial incentives for taking part in the study. Before accessing the survey, participants received an informed consent form explaining the study's purpose, the voluntary nature of participation, and data confidentiality. The necessary ethical approval was obtained from the relevant institutional ethics committee before starting data collection.

2.4 Data analysis

In this study, conducted to identify subgroups with a homogeneous structure within groups and a heterogeneous structure between groups based on Year 8 pupils' achievement levels in core subjects, LPA was used in the data analysis process. For LPA, the "tidyLPA" package (Rosenberg *et al*., 2018) available in R (R Core Team, 2023) software was utilized. To examine local independence, correlations between core subjects were analyzed. It was found that most intra-class correlations were low to moderate. Z-scores for outliers were checked, and seven participants with outliers outside the ±3 range were removed from the dataset. LPA was applied to a group of 314 individuals.

In the process of determining the most appropriate model, all solutions were comparatively evaluated, starting from a single-class model and proceeding sequentially up to a four-class model. Model selection is based on fit indices such as the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Sample Size-Corrected BIC (aBIC) (Lanza *et al*., 2003). The literature emphasizes that, particularly in small and medium-sized samples, the BIC value is the most reliable indicator and that the model with the lowest BIC value should be preferred (Nylund-Gibson & Choi, 2018). Furthermore, when selecting models, consideration should be given not only to statistical indices but also to the theoretical interpretability of the classes and the representativeness of each class within the population (Lanza *et al*., 2003). The fit indices for the models are presented in Table 1.

Table 1

Model comparisons

NO	Model	Classes	LogLik	Parameters	n	AIC	AWE	BIC	CAIC	CLC	KIC
1	2	4	-6587	51	314	13276	13912	13467	13518	13176	13330
2	2	3	-6677	38	314	13429	13902	13572	13610	13355	13470
3	6	2	-6647	85	314	13465	14525	13784	13869	13297	13553
4	6	3	-6555	128	314	13365	14963	13845	13973	13111	13496
5	2	2	-6863	25	314	13776	14087	13870	13895	13728	13804
6	1	4	-6887	33	314	13840	14251	13964	13997	13776	13876
7	1	3	-6917	26	314	13886	14210	13984	14010	13836	13915
8	3	2	-6870	49	314	13839	14450	14023	14072	13743	13891
9	6	4	-6527	171	314	13397	15532	14038	14209	13057	13571
10	3	3	-6870	56	314	13853	14552	14063	14119	13742	13912
11	3	4	-6852	63	314	13830	14616	14066	14129	13705	13896
12	1	2	-7023	19	314	14084	14319	14155	14174	14047	14106

Table 1 shows that the four-class solution offers the best fit. The entropy value and posterior probabilities—which are key indicators of analysis quality and classification accuracy—demonstrate how well the model assigns individuals to distinct classes (Hancock *et al*., 2019). The entropy value of .907 for the selected model indicates high accuracy in assigning individuals to latent profiles. Likewise, posterior class membership probabilities ranging from .944 to .971 support the reliability of these class assignments. In the four-class solution, the smallest group accounts for 12.1%, while the largest makes up 35.2%. The Bootstrap Likelihood Ratio Test produced a significant result ($p < .001$), confirming that the four-class model is statistically superior to models with fewer classes in capturing the dataset's latent structure. An analysis of the resulting profiles appears in the findings section.

To analyze which variables explain the achievement groups identified through the latent profile analysis, ordered logistic regression was used in the subsequent step. The four-category ordered profile variable, representing students' achievement levels, served as the dependent variable. Class size, whether students received private tutoring, and the number of books at home were included as independent variables. The model fit indices are shown in Table 2.

Table 2

Fit and explanatory statistics for the fitted logit model

Indicator group	İstatistik	Value	df	p
Model comparison	-2 Log Likelihood (Intercept-only model)	371,578		
	-2 Log Likelihood (Final model)	68,179		
	Model chi-square (χ^2)	303,400	4	,0001
Residual-based fit	Pearson χ^2	22,184	23	,509
	Deviance χ^2	17,898	23	,763
Pseudo R^2	Cox and Snell R^2	0,619		
	Nagelkerke R^2	0,667		
	McFadden R^2	0,365		

Table 2 indicates that the model is significant. The assumption of parallel lines, a key assumption of ordinal logistic regression analysis, was also tested; the chi-square value was 10,115 with 23 degrees of freedom, and the p-value was greater than .05. It was concluded that the slope coefficients remained constant across the response categories and that the assumption of parallel lines was satisfied. Therefore, the data were considered appropriate for ordinal logistic regression analysis. The results of the ordered logistic regression model are presented in the findings section.

3 RESULTS

3.1 Findings regarding LCA

The key findings from the profiles identified through latent profile analysis are shown in Table 3.

Table 3

Basic Course Levels for Profiles

Profile	Course	Mean	Standard deviation
1. Profile	Turkish	83.1	7.87
n=97 (30.2%)	Mathematics	60.0	10.25
	Science	68.3	8.31
	Social Studies	66.0	14.97
	Foreign Language	68.6	13.23
	Religious Studies	75.9	12.41
2. Profile	Turkish	91.1	4.83
n=113 (35.2%)	Mathematics	79.1	10.15
	Science	85.3	6.12
	Social Studies	81.1	11.83

	Foreign Language	81.1	12.17
	Religious Studies	86.1	8.70
3.Profile n=71 (22.1%)	Turkish	95.9	2.03
	Mathematics	93.1	5.55
	Science	94.3	3.82
	Social Studies	90.6	7.89
	Foreign Language	89.6	6.56
	Religious Studies	94.0	4.44
4.Profile n=40 (12.1%)	Turkish	97.6	1.59
	Mathematics	98.9	1.44
	Science	98.1	2.08
	Social Studies	98.2	2.20
	Foreign Language	96.9	2.47
	Religious Studies	98.3	1.79

An analysis of Table 3 shows that the distribution of profiles within the group is fairly even. Individuals with Profile 1 make up 30.2% of the group (n=97), those with Profile 2 account for 35.2% (n=113), Profile 3 comprises 22.1% (n=71), and Profile 4 represents 12.1% (n=40). The fact that no group is smaller than 10% or larger than 40% of the total sample indicates that the profiles reflect a balanced participant group. To visually examine the distribution across participants, a box plot showing profile distribution across core subjects is shown in Figure 1.

Figure 1

Box plot for courses

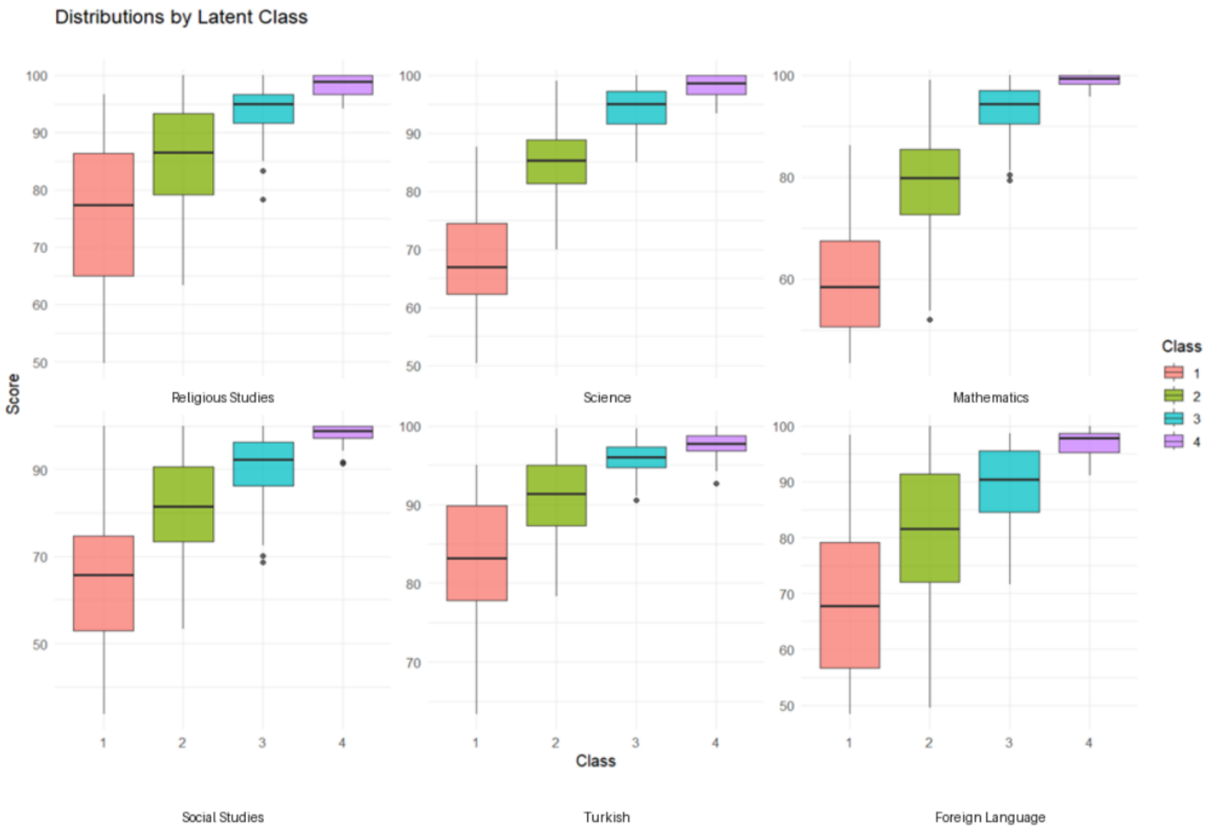

Figure 1 shows the distribution of core subject marks across latent classes. When looking at the figure as a whole, a consistent achievement pattern emerges across the profiles, ranging from low to high. The first profile indicates the lowest level of academic performance, while the fourth profile indicates the highest. Box plots reveal that the differentiation between profiles is not consistent across all subjects; some subjects differentiate the profiles more clearly, while in others, the distributions are more similar. Additionally, it is clear that variability is higher in low-achieving profiles, whereas scores tend to be more clustered and uniform in high-achieving profiles. An ordered logistic regression was conducted to assess how much class size, the number of textbooks, and private tuition status explain the profiles derived from the research. The results are shown in Table 4.

Table 4

			B	Sh	Wald	df	p	95% Confidence Interval CI Lower	Upper
Threshold	Group	1.profile	-,879	,221	15,848	1	,0001	-1,312	-,446
		2.profile	1,892	,270	49,035	1	,0001	1,362	2,421
		3.profile	6,810	1,035	43,294	1	,0001	4,781	8,838
Location	Class size	between 30 and 40	6,836	1,029	44,118	1	,0001	4,819	8,853
		more than 40	0[a]	.	.	0	.	.	.
	The situation regarding private lessons	Yes, I'll take it	-,250	,237	1,113	1	,292	-,714	,214
		No, I'm not	0[a]	.	.	0	.	.	.
	Number of books	0-25 books	-2,267	,514	19,467	1	,0001	-3,274	-1,260
		26-100 books	-,249	,262	,899	1	,343	-,763	,265
		Over 100 books	0[a]	.	.	0	.	.	.

Table 4 presents the B-coefficients, Wald coefficients, p-values, and confidence intervals for the variables included in the model. When examining the p-values to determine whether the variables' contributions to the model are significant, it is observed that having a class size of 30–40 significantly explains individuals' certificate attainment, Wald = 44,118, $p < .05$. Regarding the direction of this effect, a positive effect is noted, B = 6.836; being in a class with 30–40 students increases success by 83 units (95% CI, 4.819 to 8.853). It was found that whether individuals took private tuition was not a significant predictor of certificate attainment, Wald = 1.113, $p > .05$. Having between 0 and 25 books significantly explained certificate attainment, Wald = 19,467, $p < .05$. The effect was negative, B = -2.267, indicating that owning 0- 25 books reduces academic achievement by 2.26 units compared to owning 26–100 books (95% CI, -3.274 to- 1.260). However, owning 26–100 books does not significantly explain academic achievement compared to owning more than 100 books, Wald = -0.249, $p > .05$. The results related to the accuracy of classification performed using the proposed model are presented in Table 5.

Table 5

Accuracy of the Logit Model

			Group			
			1.profile	2.profile	3.profile	4.profile
Predict group	1.profile	n	24	66	0	0
		%	26.7%	73.3%	0.0%	0.0%
	2.profile	n	4	108	0	1
		%	3.5%	95.6%	0.0%	0.9%
	3.profile	n	1	21	37	12
		%	1.4%	29.6%	52.1%	16.9%
	4.profile	n	0	0	34	6
		%	0.0%	0.0%	85.0%	15.0%

The model's classification results are presented in Table 5. To find the accuracy rate, the number of individuals correctly classified in each category was divided by the total number of participants. The accuracy rate calculated in this manner was 55.7%. This outcome suggests that the model performed better than chance. The model classified the second-best profile most accurately and the fourth-lowest profile least accurately.

4 DISCUSSION, CONCLUSION, AND RECOMMENDATIONS

This study aimed to identify the academic profiles of Year 8 students based on their performance in core subjects and to analyze how these profiles differ concerning educational and socio-cultural factors. The findings suggest that a four-class profile structure, derived from core subject achievement, provides the best fit. According to the literature, latent class analyses are more sensitive in revealing inter-individual differences than traditional measurement methods (Porcu & Giambona, 2017). The ordinal logistic regression results examining the impact of various variables on the profiles show that class size and the number of books owned are significant predictors, supporting the idea that academic achievement is influenced by contextual and socio-cultural factors beyond individual ability (Sideridis *et al*., 2021). It was observed that the subject in which profiles showed the least variation in achievement levels was Turkish, while the subjects with the greatest differences were mathematics and foreign languages.

In analyses conducted by subject, the fact that Turkish scores were relatively high across all profiles and that its ability to distinguish between groups remained at the lowest level suggests that basic language skills are a common achievement area for students at this age. However, from a methodological perspective, low intra-profile variance for a variable limits its capacity to differentiate between classes (Haertel, 1984). Conversely, it is noteworthy that mathematics and foreign language courses are the subjects that show the highest level of heterogeneity between profiles. In particular, the fact that mathematics achievement is identified as the lowest-performing area within the first profile confirms that this subject is a critical indicator of academic risk (King *et al*., 2016). This significant variation in mathematics achievement aligns with data from large-scale international exams and emphasizes the importance of numerical skills in distinguishing student profiles (Toker & Green, 2021). The distribution of performance in foreign language lessons also shows a similar pattern, emerging as a key factor in forming these profiles.

The consistent and growing achievement hierarchy seen in science and social studies shows these subjects effectively differentiate students at lower-middle and upper-middle achievement levels. The fact that significant differences between lower-achieving groups in science begin to even out within high-achieving groups aligns with theories suggesting that academic satisfaction is achieved beyond a certain point (Kim, 2023).

Similarly, in social studies and religious culture lessons, the fact that achievement remains quite stable and high in the top profiles indicates that these subjects are common strengths for students with high academic ability. From a psychometric point of view, such classifications show not only how successful students are but also which subject components influence their success (Hancock *et al*., 2019). As a result, it is understood that subjects like Turkish and religious culture have similarities across profiles, while subjects like mathematics and foreign languages clearly separate students into different academic profiles. This situation highlights that educational interventions should focus on the subjects that most strongly differentiate profiles and are key points of academic risk, rather than being success-focused overall.

The results of the ordered logistic regression show that students' placement in higher or lower academic profiles cannot be explained solely by individual performance differences. Instead, contextual factors related to the school and home environment play a crucial role. Notably, the emergence of class size as a significant factor suggests that learning is influenced not only by individual traits but also by classroom interactions and teaching practices. Although the research on how class size affects academic achievement shows mixed results, it is understood that class structure can impact teacher attention, student participation, and learning opportunities. This can lead to indirect but meaningful effects on achievement (Shin & Raudenbush, 2011). From this perspective, the fact that class size significantly explains profile transitions in this study highlights the importance of considering the structural conditions within schools that shape academic success.

The fact that the number of books at home is a significant explanatory factor supports the idea that academic success is closely linked to cultural capital and home-based learning resources. The presence of books at home is often seen in the literature as an indirect indicator of the student's cultural and educational environment. The literature emphasizes that the number of books at home is strongly related to achievement but also highlights the need for careful interpretation (Engzell, 2021). However, findings indicating that reading habits and a home-based literary environment support students' verbal and overall academic development suggest that the home book and reading culture provides an important foundation for developing achievement patterns (Park, 2008). The current study's finding that having fewer books is associated with lower achievement profiles suggests that inequalities in achievement are affected not only by factors within schools but also by the cultural opportunity structures at home.

Conversely, the fact that receiving private tuition is not a statistically significant explanatory factor is noteworthy because it shows that private tuition does not always lead to higher achievement levels for all students. Recent studies on the impact of private tuition suggest that this support is often limited, dependent on context, or effective only for certain groups of students. In particular, longitudinal research indicates that regular private tuition contributes only slightly to mathematics achievement or fails to produce a meaningful and consistent effect (Zhang *et al*., 2021). Some recent findings even suggest that increasing the number of private tuition sessions could lead to negative outcomes on overall achievement (Zhang *et al*., 2025). Therefore, the fact that the private tuition variable was not significant in this study highlights that short-term external support has limited ability to improve students' overall academic performance.

Overall, the results of the ordered logistic regression confirm the cumulative impact of socio-ecological factors in shaping academic achievement profiles. It seems that reaching higher academic profiles depends not only on individual effort or external support but also on a high-quality classroom environment, home-based cultural resources that encourage learning, and sustainable educational opportunities. This finding emphasizes the need for education policies to focus not just on short-term interventions aimed at increasing individual achievement but also on more structural reforms that strengthen the learning ecosystem in which students are part.

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