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Neighborhoods and Schools: The Socio-Spatial Dynamics of Educational Achievement in Amsterdam

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Abstract

Background/purpose. This study investigates how neighborhood dynamics and school characteristics intersect to influence the academic achievement of primary school students in Amsterdam. By exploring the effects of urbanization, gentrification, and segregation, the study examines the socio-spatial factors shaping disparities in educational performance at both fundamental and target levels.

Materials/methods. The study analyzed data from 181 schools across 146 neighborhoods, sourced from publicly available datasets. Stepwise regression was used to identify significant predictors, and hierarchical regression was applied to examine the combined effects of neighborhood and school-level factors on academic achievement.

Results. The findings reveal that disparities in academic achievement are primarily influenced by school-level factors, such as the percentage of students in higher academic tracks (HAVO/VWO) and the concentration of students in vocational education with the lowest academic level. Income levels and population density further shape the socio-economic composition of neighborhoods and schools, amplifying existing inequalities.

Conclusion. The study underscores the importance of integrated urban and educational policy approaches to mitigate the effects of segregation and promote equitable access to quality education. Recommendations include the redistribution of socio-economic resources across neighborhoods and targeted interventions for schools in disadvantaged areas.

1. Introduction

Academic achievement is a multifaceted phenomenon shaped by a combination of individual, institutional, and environmental factors. While much of the focus in educational research has centered on in-school elements such as teaching quality, leadership practices, and student engagement, the broader spatial and social contexts in which schools operate remain underexplored. The neighborhoods surrounding schools are not just physical spaces; they are socio-economic and cultural ecosystems that deeply influence student populations, teacher distribution, and resource allocation. These neighborhood-level dynamics often set the stage for disparities in educational outcomes, making them an essential yet often overlooked area of inquiry.

Existing research on neighborhood effects consistently underscores the significant role that local conditions play in shaping educational trajectories and career opportunities. Studies reveal that neighborhood characteristics influence students' career aspirations (Bauder, 2001), school selection processes (Warrington, 2005), and disparities in educational performance, which, in turn, impact long-term economic prospects (Andersson & Subramanian, 2006; Galster et al., 2007; Karakose et al., 2025a; Massey & Fischer, 2006). Evidence from cross-national studies has linked neighborhood conditions to education length (Duncan, 1994), dropout rates (Crowder & South, 2003), and standardized exam performance (Ainsworth, 2002). In the Netherlands, Sykes (2011) revealed that a school's socioeconomic status has a more profound impact on student outcomes than its ethnic composition, challenging assumptions about the relative influence of demographic factors.

Urban infrastructures, including educational institutions, healthcare facilities, libraries, and childcare centers, further mediate the relationship between neighborhoods and student composition. To understand these dynamics in detail, this study examines six categories of urban functions—economy, security, health, demography, education, and energy consumption—using 25 indicators. The analysis investigates 181 schools across 146 neighborhoods in Amsterdam to uncover how spatial segregation influences academic achievement.

In addition to neighborhood-level variables, school-specific factors, such as student population size, grade retention rates, and teacher employment stability, are incorporated into the analysis. Educational tracks, including practical education (Praktijkonderwijs), vocational pathways (VMBO, HAVO, VWO), and other school attributes, are analyzed using recent data from 2022 to ensure robustness. These elements complement the broader literature, which highlights how neighborhood characteristics shape not only student composition but also staffing patterns and resource distribution.

This research employs a hierarchical analytical approach to identify the drivers of academic achievement disparities. The first phase explores how neighborhood characteristics influence educational targets, while the second phase evaluates the effects of school-specific variables. Finally, a combined hierarchical regression analysis examines the interaction of neighborhood and school factors, identifying those that most significantly impact academic success. By adopting this layered methodology, the study aims to provide a nuanced understanding of the socio-spatial factors affecting educational outcomes, offering valuable insights for both urban planning and education policy.

2. Literature Review

The concept of neighborhood effects provides a critical lens for understanding how the characteristics of neighborhoods shape individuals' opportunities in education, employment, and broader social behaviors. These effects operate through various mechanisms—endogenous, correlational, and contextual (Dietz, 2002)—illustrating that neighborhood conditions can have immediate and long-term consequences for residents. Processes such as urbanization, segregation,

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and gentrification significantly contribute to the disparities observed among neighborhoods, creating distinct socio-economic, demographic, and cultural profiles across urban landscapes.

Urbanization, a process characterized by population growth in urban areas, reshapes neighborhood dynamics by influencing migration patterns and the development of infrastructure (Havighurst, 1967; Jenkins, 2013). Its impact, however, depends on management strategies—planned urbanization can foster opportunities, whereas unregulated growth often amplifies inequalities, leaving neighborhoods with starkly contrasting resources and risks. Segregation furthers these disparities by clustering populations based on socioeconomic, ethnic, or demographic characteristics (Karsten et al., 2006; Karakose et al., 2025b; Oberti, 2007), often leading to unequal access to education and employment opportunities. As a complementary phenomenon, gentrification transforms economically disadvantaged neighborhoods by attracting higher-income residents, driving up housing prices, and displacing long-standing, low-income populations. This reconfiguration alters the social fabric of neighborhoods, often exacerbating inequalities and reducing diversity (Forster, 2006; Uitermark, 2003).

These three processes—urbanization, segregation, and gentrification—are deeply interconnected. Segregation often lays the groundwork for gentrification by creating homogenous neighborhoods that sustain structural inequalities, while gentrification intensifies disparities through displacement. Together, these processes contribute to long-term cycles of disadvantage. For instance, Wilson's (2012) concept of concentrated poverty emphasizes how the spatial clustering of low-income households perpetuates educational and employment inequities, reinforcing socio-economic divides over time.

Neighborhood disparities significantly influence both education and employment outcomes. High-income neighborhoods provide access to quality schools, skilled teachers, and influential social networks, which together promote academic success (Kauppinen, 2007; Karakose & Polat, 2025). Conversely, disadvantaged neighborhoods often lack institutional support, channeling students toward low-wage jobs with limited career growth (Bauder, 2001). Kuyvenhoven and Boterman (2021) demonstrated that in Amsterdam, students from affluent neighborhoods are more likely to access academically rigorous tracks, such as HAVO or VWO, whereas students from lower-income areas face structural barriers in educational placement.

Similarly, employment opportunities are heavily shaped by neighborhood contexts. In low-income neighborhoods, local networks may provide immediate support but often restrict long-term mobility due to limited skill development and exposure (Pinkster, 2007). In contrast, wealthier areas not only offer access to better job markets but also foster upward mobility through connections and mentorship opportunities. This dual impact of neighborhood contexts on education and employment underscores the cyclical nature of inequality, where disadvantages in one domain reinforce challenges in the other.

While neighborhood disparities are globally pervasive, their manifestations differ based on regional and historical contexts. In the United States, urban sprawl and historical redlining policies have entrenched segregation, while European cities like Amsterdam and Paris experience more subtle forms of socio-spatial inequality due to zoning regulations and immigration patterns (Pinkster & Boterman, 2017). In rapidly urbanizing regions of South Asia and Sub-Saharan Africa, informal settlements and unregulated growth exacerbate disparities in education and healthcare access (United Nations, 2016). Despite these regional differences, the underlying dynamics of spatial inequality remain consistent: socio-economic conditions in neighborhoods shape educational and employment opportunities, often perpetuating intergenerational disadvantage.

In the Netherlands, Zorlu and Latten (2009) highlighted how housing policies amplify these disparities, with low-income, non-Western immigrant populations disproportionately concentrated in older, affordable urban areas. These patterns of residential segregation affect not only education and employment but also collective trust, crime rates, and public health. High-income neighborhoods generally enjoy lower crime rates and better environmental services, whereas low-income areas face inadequate infrastructure, higher stress levels, and poor health outcomes (Sampson et al., 2002).

Housing markets play a pivotal role in reinforcing neighborhood disparities. Property values act as a socio-economic filter, shaping who can afford to live in specific areas. Wealthier families often migrate to neighborhoods with better schools, driving up property prices and further restricting access for low-income groups (Francis & Hutchings, 2013). Enrollment zones and school catchment policies codify these exclusions, limiting opportunities for disadvantaged students (Hamnett & Butler, 2011). Moreover, the socio-economic composition of neighborhoods directly influences educational trajectories. Wealthier areas, with predominantly privately owned housing, support better schools and programs, while working-class neighborhoods, with higher concentrations of public housing, struggle with limited resources (Oberti, 2007).

The combined effects of urbanization, segregation, and gentrification shape educational opportunities in significant ways. Socio-economic resources within neighborhoods, such as the proportion of educated residents or access to skilled teachers, profoundly influence students' educational outcomes (Andersson & Subramanian, 2006). Disadvantaged neighborhoods face higher dropout rates and reduced academic performance due to insufficient institutional support and the compounding effects of poverty (Lupton, 2005). Lupton emphasized that addressing these challenges requires systemic changes that consider the broader socio-economic contexts of schools. Without such reforms, schools in disadvantaged areas face substantial barriers to sustainable improvement, as they are forced to balance academic goals with addressing students' non-academic needs.

This study builds on the neighborhood effects framework to explore the intersection of urban dynamics and education in Amsterdam. By analyzing how urbanization, housing, and school-specific factors interact, this research aims to identify actionable strategies for reducing educational inequities in urban settings. To achieve this aim, the following research questions were developed:

1. What neighborhood-level characteristics significantly influence fundamental academic achievement in primary schools in Amsterdam?

2. Which school-level characteristics significantly predict fundamental academic achievement in primary schools in Amsterdam?

3. What are the combined effects of neighborhood-level and school-level characteristics on fundamental academic achievement in primary schools in Amsterdam?

4. What neighborhood-level characteristics significantly influence target-level academic achievement in primary schools in Amsterdam?

5. Which school-level characteristics significantly predict target-level academic achievement in primary schools in Amsterdam?

6. What are the combined effects of neighborhood-level and school-level characteristics on target-level academic achievement in primary schools in Amsterdam?

3. Methodology

3.1. Research Model

In this study, the dataset was compiled from two primary sources. Data related to academic achievement—our dependent variables—were obtained from the "fundamental level" and "target level" data sections of Scholenopdekaart.nl. The fundamental level represents the basic competencies in language and arithmetic that most students are expected to achieve by the end of

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primary school. This metric is assessed through the final examination in group eight, with the Dutch Inspectorate of Education setting an 85% threshold as the minimum acceptable attainment rate for all primary schools in the Netherlands. The target level, a more ambitious benchmark, indicates the proportion of students expected to achieve advanced competencies by the end of group eight. For each school, the Inspectorate determines a specific target percentage based on the characteristics of the student population. These percentages serve as the dependent variables in our analysis.

For this study, schools in Amsterdam were identified through a keyword search for "Amsterdam" combined with the "primary school" filter on Scholenopdekaart.nl. Schools meeting the inclusion criteria were selected, with 181 schools from 146 neighborhoods ultimately included in the dataset. Excluded schools comprised those lacking complete neighborhood or school-specific data and institutions classified under Voortgezet Speciaal Onderwijs (special secondary education).

Independent variables in the study were drawn from neighborhood-level urbanization data sourced from Allecijfers.nl. These variables include socioeconomic, demographic, health, security, education, and energy-related indicators. A total of 25 indicators were selected based on their relevance to urbanization and their presence in the literature. To ensure consistency, data from 2022 were used for all schools and neighborhoods. This dataset reflects the conditions that influence the educational landscape, such as overcrowded classrooms, teacher shortages, and variations in student performance.

3.2. Data Analysis

The analysis utilized two dependent variables—fundamental and target levels of academic achievement—to comprehensively evaluate educational performance. While the fundamental level reflects basic competency standards, the target level captures higher-order achievement, offering a more nuanced view of academic success. This dual-variable approach allows the study to examine factors influencing both minimal and exceptional educational outcomes.

The methodological framework was structured in three stages. First, stepwise regression was employed to explore the relationship between each dependent variable and neighborhood characteristics, identifying statistically significant factors. Second, a similar stepwise regression analysis was conducted for school-specific variables. Finally, hierarchical regression was applied to assess the combined influence of neighborhood and school-level predictors. This layered approach provides insights into the extent to which neighborhood characteristics influence school composition and academic performance.

Stepwise regression, utilizing forward selection, automated the identification of significant predictors by iteratively adding variables that most improved model fit (Draper & Smith, 1998; Field, 2005). This method was particularly suited for the complex dataset, allowing for the selection of key variables among the numerous urbanization indicators. Hierarchical regression further complemented this approach by sequentially introducing predictors to evaluate their incremental contribution to explaining variations in academic achievement (Field, 2005). This method enabled the study to disentangle the distinct and overlapping effects of neighborhood and school factors on academic success.

Prior to conducting the analyses, the dataset underwent extensive preprocessing to ensure that statistical assumptions were met. Multicollinearity was addressed by removing variables with high correlations, with tolerance values above .20 and VIF values below 10 considered acceptable. Autocorrelation was evaluated using the Durbin-Watson test, with scores between 1 and 3 deemed satisfactory. Outlier detection was performed using Mahalanobis Distance, ensuring the validity of the dataset (Cook & Weisberg, 1982; Craney & Surles, 2002). Variables that did not meet the normality assumption, such as "the proportion of individuals aged 15-25 in the neighborhood," "annual traffic accident count," "annual student population," and "the number of students directed to practical and special education," were excluded from the analysis. Additionally, the Apollobuurt neighborhood and Europaschool were identified as outliers and therefore excluded from the study to maintain the robustness of the results.

The indicators for housing sales prices and health satisfaction were excluded from the analysis due to high correlations with average income per resident, which could lead to multicollinearity. Housing sales prices showed a strong positive correlation with income ($r = 0.883$, $p < 0.01$) and health satisfaction ($r = 0.678$, $p < 0.01$). Similarly, health satisfaction exhibited a strong positive correlation with income ($r = 0.803$, $p < 0.01$). These correlations highlight gentrification dynamics, where wealthier neighborhoods with higher property values and better health outcomes further reflect socio-economic stratification within urban spaces.

4. Results

4.1. Fundamental Level Achievement

To explore the neighborhood effects on academic achievement, we began by examining the relationship between neighborhood indicators and fundamental-level academic achievement using stepwise regression. This initial analysis aimed to identify the significant neighborhood-level variables associated with basic academic success. Next, we conducted a stepwise regression analysis focusing on the relationship between fundamental-level academic achievement and school-specific indicators, identifying key school-level predictors. Finally, we integrated the significant variables from both analyses into a hierarchical regression model. In this final model, neighborhood and school indicators were combined as independent variables, with fundamental-level academic achievement serving as the dependent variable, allowing us to evaluate their combined and relative contributions to academic success.

4.1.1. Mapping Neighborhood Dynamics: Unraveling the Foundations of Academic Success

To explore how neighborhood dynamics influence education, stepwise linear regression analysis was employed to assess the relationship between fundamental academic achievement and urban indicators of neighborhoods. A summary of the resulting model is presented below.

Table 1. Neighbourhood Effect and Fundamental Level Analysis Model Summary

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.441[a]	.195	.190	3.7014	.195	42.105	1	174	.000	
2	.466[b]	.217	.208	3.6609	.022	4.872	1	173	.029	1.993

a. Predictors: (Constant), Het aandeel migranten in de totale bevolking (Non-westers)

b. Predictors: (Constant), Het aandeel migranten in de totale bevolking (Non-westers), Dichtheid per km2 van auto's

c. Dependent Variable: Fundamenteel niveau

As shown in Table 1, the model accounts for approximately 21.7% of the variance in the dependent variable. The Durbin-Watson statistic of 1.993, being close to 2, suggests that there is no evidence of autocorrelation in the residuals. Table 2 provides the coefficients associated with the model.

Table 1. Neighbourhood effect on fundamental level achievement

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	98.428	.680		144.785	.000	97.086	99.770					
	Het aandeel migranten in de totale bevolking (Non-westers)	-.096	.015	-.441	-6.489	.000	-.125	-.067	-.441	-.441	-.441	1.000	1.000
2	(Constant)	96.906	.963		100.621	.000	95.005	98.807					
	Het aandeel migranten in de totale bevolking (Non-westers)	-.092	.015	-.426	-6.299	.000	-.121	-.063	-.441	-.432	-.424	.989	1.011
	Dichtheid per km2 van auto's	.000	.000	.149	2.207	.029	.000	.001	.193	.166	.149	.989	1.011

a. Dependent Variable: Fundamenteel niveau

The stepwise regression analysis results indicate that the proportion of non-Western migrants in a neighborhood is a significant predictor of fundamental-level academic achievement (B = -0.096, β = -0.441, $p < 0.001$), explaining 19.5% of the variance ($R^2 = 0.195$). Adding the variable "density of cars per square kilometer" (B = 0.000, β = 0.149, $p = 0.029$) in the second model increased the explained variance to 21.7% ($R^2 = 0.217$). While the proportion of non-Western migrants remained significant (B = -0.092, β = -0.426, $p < 0.001$), its impact slightly diminished, suggesting a partial mediation effect by car density. The Durbin-Watson statistic of 1.993 indicates no autocorrelation in the residuals, and collinearity diagnostics (Tolerance = 0.989, VIF = 1.011) confirm the absence of multicollinearity. These results underscore the influence of both demographic and infrastructural neighborhood characteristics on fundamental academic achievement.

4.1.2. School Characteristics and Their Impact on Fundamental Academic Achievement

The second phase of analysis explored the connection between school-specific factors and fundamental academic achievement rates. A summary of the model is presented below.

Table 3. Model summary of the analysis for school characteristics and fundamental level achievement

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.679[a]	.462	.459	3.0330	.462	151.733	1	177	.000	
2	.696[b]	.484	.478	2.9776	.022	7.646	1	176	.006	
3	.716[c]	.513	.505	2.9009	.029	10.427	1	175	.001	
4	.726[d]	.527	.516	2.8664	.014	5.239	1	174	.023	
5	.738[e]	.545	.532	2.8204	.018	6.720	1	173	.010	
6	.747[f]	.557	.542	2.7899	.012	4.811	1	172	.030	1.978

This model summary illustrates the progressive inclusion of school-level variables in predicting fundamental academic achievement. The analysis begins with the percentage of students enrolled in vocational education programs with the lowest academic level (% beroepskader) as a significant predictor ($R^2 = 0.462$), explaining 46.2% of the variance. Adding the percentage of students continuing to HAVO/VWO tracks (% HAVO/VWO), which includes students eligible for higher general secondary education (HAVO) and pre-university education (VWO), increases the explained variance to 48.4% (R^2 change = 0.022, $p = 0.006$). The third step incorporates the percentage of students in VWO tracks (% VWO), representing those pursuing pre-university education, further improving the model's predictive power to 51.3% (R^2 change = 0.029, $p = 0.001$).

Subsequent steps introduce additional variables, including the percentage of temporary staff (Het percentage tijdelijk personeel), full-time equivalent employees (0.8 FTE+), and the percentage of students in VMBO tracks (% VMBO), which refers to vocational secondary education encompassing multiple levels. These additions collectively increase the model's explanatory capacity to 55.7% ($R^2 = 0.557$). The Durbin-Watson statistic of 1.978 suggests no significant autocorrelation in the residuals. The coefficients are presented in Table 4.

Table 2. The association of school characteristics and fundamental level achievement

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
6	(Constant)	94.841	1.711		55.416	.000	91.463	98.219					
	% beroepskader	-.105	.024	-.361	-4.367	.000	-.153	-.058	-.679	-.316	-.222	.377	2.653
	% HAVO VWO	.110	.032	.219	3.414	.001	.047	.174	.470	.252	.173	.624	1.602
	% VWO	.081	.021	.326	3.886	.000	.040	.123	.577	.284	.197	.367	2.727

The final hierarchical regression model results, presented in Table 4, indicate that several school-level variables significantly predict fundamental academic achievement, collectively explaining 55.7% of the variance ($R^2 = 0.557$). The percentage of students in vocational education with the lowest academic level (% beroepskader) negatively impacted achievement (B = -0.105, β = -0.361, $p < 0.001$), highlighting the challenges faced by schools with a higher proportion of students in this category. Conversely, the percentage of students in higher academic tracks, such as HAVO/VWO (B = 0.110, β = 0.219, p = 0.001) and VWO (B = 0.081, β = 0.326, $p < 0.001$), positively contributed to achievement. Staffing variables also influenced outcomes, with the percentage of temporary staff (B = -0.056, β = -0.140, p = 0.007) and full-time equivalent staff (B = -0.034, β = -0.143, p = 0.007) both showing negative associations. Interestingly, the percentage of students in VMBO tracks, representing vocational secondary education, positively affected achievement (B = 0.075, β = 0.142, p = 0.030). These findings underscore the combined importance of student composition and staffing conditions in shaping fundamental academic success. The Durbin-Watson statistic of 1.978 and acceptable collinearity diagnostics confirm the robustness of the model.

4.1.3. Unveiling Intersections: Hierarchical Insights into Neighborhood and School Dynamics

The hierarchical regression analysis was conducted to examine the combined effects of neighborhood and school-level variables on fundamental academic achievement. The results, summarized in Table 5, demonstrate the incremental contributions of these predictors to the explained variance in achievement outcomes.

Table 5. Neighborhood and school analysis on fundamental level model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.475[a]	.226	.217	3.6475	.226	25.646	2	176	.000	
2	.749[b]	.561	.541	2.7931	.336	21.691	6	170	.000	1.983

The first model, which includes neighborhood-level predictors such as car density per square kilometer and the proportion of non-Western migrants in the population, explains 22.6% of the variance in fundamental academic achievement ($R^2 = 0.226$, $p < 0.001$). The addition of school-level variables in the second model, including staff composition (0.8 FTE+, percentage of temporary staff), and student distribution across educational tracks (% VMBO, % HAVO/VWO, % beroepskader, % VWO), significantly increases the explained variance to 56.1% (R^2 change = 0.336, $p < 0.001$). The coefficients are provided in Table 6.

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Table 3. Neighborhood and school level coefficients on fundamental level

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	97.067	.949		102.237	.000	95.193	98.940					
	Het aandeel migranten in de totale bevolking (Non-westers)	-.095	.014	-.439	-6.579	.000	-.124	-.067	-.453	-.444	-.436	.990	1.010
	Dichtheid per km2 van auto's	.000	.000	.145	2.169	.031	.000	.001	.188	.161	.144	.990	1.010
2	(Constant)	94.966	1.959		48.477	.000	91.099	98.834					
	Het aandeel migranten in de totale bevolking (Non-westers)	-.012	.014	-.056	-.905	.367	-.039	.014	-.453	-.069	-.046	.664	1.505
	Dichtheid per km2 van auto's	.000	.000	.047	.890	.375	.000	.000	.188	.068	.045	.945	1.059
	Het percentage tijdelijk personeel ten opzichte van het totale personeel	-.054	.021	-.136	-2.620	.010	-.095	-.013	-.196	-.197	-.133	.955	1.047
	0,8 FTE+	-.033	.012	-.141	-2.685	.008	-.057	-.009	-.219	-.202	-.136	.940	1.064
	% beroepskader	-.099	.025	-.339	-3.998	.000	-.147	-.050	-.679	-.293	-.203	.360	2.780
	% HAVO VWO	.108	.033	.214	3.283	.001	.043	.173	.470	.244	.167	.607	1.648
	% VWO	.076	.022	.303	3.494	.001	.033	.119	.577	.259	.177	.343	2.915
	% VMBO	.071	.034	.136	2.077	.039	.004	.139	-.265	.157	.105	.604	1.655

a. Dependent Variable: Fundamenteel niveau

The hierarchical regression analysis results reveal that both neighborhood and school-level variables significantly contribute to fundamental academic achievement, with school-level factors playing a more prominent role in the final model. In the first model, neighborhood-level predictors, including the proportion of non-Western migrants (B = -0.095, β = -0.439, $p < 0.001$) and car density per square kilometer (B = 0.000, β = 0.145, $p = 0.031$), were significant, explaining a portion of the variance. However, these effects diminished when school-level variables were introduced in the second model. Key school-level predictors included the percentage of students in lower-level vocational tracks (% beroepskader, B = -0.099, β = -0.339, $p < 0.001$), which negatively influenced achievement, and the percentage of students in higher academic tracks, such as HAVO/VWO (B = 0.108, β = 0.214, $p = 0.001$) and VWO (B = 0.076, β = 0.303, $p = 0.001$), which positively impacted outcomes. Staffing-related variables also played a significant role, with higher proportions of temporary staff (B = -0.054, β = -0.136, $p = 0.010$) and full-time equivalent staff (B = -0.033, β = -0.141, $p = 0.008$) negatively affecting achievement. These findings underscore the mediating influence of school-level factors on neighborhood effects, highlighting the critical importance of student composition, academic tracks, and staffing stability in shaping fundamental academic success.

4.2. Target Level Achievement

In the second part of the study, the relationship between target-level academic achievement and neighborhood and school characteristics was examined. Following the same steps as in the previous section, stepwise regression analyses were first conducted to identify significant predictors. These significant variables were then incorporated into a hierarchical regression analysis to evaluate the combined effects of neighborhood and school-level factors on target-level academic success.

4.2.1. Neighborhood Dynamics and the Pursuit of Academic Excellence

In this section, the relationship between neighborhood effects and target-level academic achievement was analyzed using stepwise regression analysis. The model summary is presented in Table 7.

Table 7. Neighborhood dynamics on target level achievement model summary

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.504[a]	.254	.250	12.7134	.254	59.280	1	174	.000	
2	.532[b]	.283	.275	12.4980	.029	7.050	1	173	.009	
3	.556[c]	.309	.297	12.3046	.026	6.482	1	172	.012	2.143

The stepwise regression analysis results, presented in Table 7, demonstrate the significant influence of neighborhood-level factors on target-level academic achievement, collectively explaining 30.9% of the variance in the final model. In the first model, average income per resident (Gemiddeld inkomen per inwoner) was identified as a significant predictor, accounting for 25.4% of the variance ($R^2 = 0.254$, $p < 0.001$), indicating that higher neighborhood income levels are positively associated with better academic outcomes. Population density per square kilometer (Dichtheid per km² van bevolking) was added in the second model, increasing the explained variance to 28.3% (R^2 change = 0.029, $p = 0.009$). Finally, the proportion of non-Western migrants in the population (Het aandeel migranten in de totale bevolking - Non-westers) was included in the third model, further improving the explained variance to 30.9% (R^2 change = 0.026, $p = 0.012$). While this demographic variable negatively correlates with target-level achievement, its inclusion highlights the multifaceted nature of neighborhood effects. The Durbin-Watson statistic of 2.143 confirms no autocorrelation in the residuals, reinforcing the robustness of the model. These findings emphasize the combined importance of socioeconomic and demographic neighborhood characteristics in shaping target-level academic success. The coefficients are are presented in Table 8.

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Table 4. Neighborhood coefficients on target level achievement

Coefficients[a]

Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
(Constant)	36.851	2.719		13.552	.000	31.484	42.218					
Gemiddeld inkomen per inwoner	.001	.000	.504	7.699	.000	.000	.001	.504	.504	.504	1.000	1.000
(Constant)	32.909	3.058		10.762	.000	26.874	38.945					
Gemiddeld inkomen per inwoner	.001	.000	.481	7.413	.000	.000	.001	.504	.491	.477	.983	1.018
Dichtheid per km2 van bevolking	.000	.000	.172	2.655	.009	.000	.001	.236	.198	.171	.983	1.018
(Constant)	47.965	6.636		7.228	.000	34.867	61.063					
Gemiddeld inkomen per inwoner	.000	.000	.302	3.177	.002	.000	.001	.504	.235	.201	.444	2.252
Dichtheid per km2 van bevolking	.000	.000	.165	2.571	.011	.000	.001	.236	.192	.163	.980	1.020
Het aandeel migranten in de totale bevolking (Non-westers)	-.187	.074	-.242	-2.546	.012	-.333	-.042	-.488	-.191	-.161	.444	2.250

a. Dependent Variable: Streefniveau

The stepwise regression analysis reveals that neighborhood-level factors significantly influence target-level academic achievement, explaining 30.9% of the variance in the final model. Average income per resident positively impacts achievement across all models (B = 0.001, β = 0.302, p = 0.002), while population density also shows a positive association (B = 0.000, β = 0.165, p = 0.011). However, the proportion of non-Western migrants negatively affects target-level achievement (B = -0.187, β = -0.242, p = 0.012).

4.2.2. School Dynamics and the Road to Academic Excellence

The stepwise regression analysis examining the relationship between school characteristics and target-level academic achievement is summarized in Table 9.

Table 9. School dynamics on target level achievement model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.709[a]	.502	.499	10.5402	.502	178.503	1	177	.000	
2	.758[b]	.575	.570	9.7664	.073	30.158	1	176	.000	
3	.774[c]	.599	.592	9.5108	.024	10.587	1	175	.001	
4	.786[d]	.618	.610	9.3080	.019	8.709	1	174	.004	2.043

The stepwise regression analysis results, summarized in Table 9, reveal that school-level characteristics significantly predict target-level academic achievement, explaining 61.8% of the variance in the final model. The percentage of students in vocational education with the lowest academic level (% beroepskader) was the strongest negative predictor in the first model ($R^2 = 0.502$, $p < 0.001$). The addition of the percentage of students in pre-university tracks (% VWO) in the second model increased the explained variance to 57.5% (R^2 change = 0.073, $p < 0.001$). Further improvements were observed with the inclusion of the percentage of students in higher academic tracks (% HAVO/VWO), and the percentage of temporary staff (Het percentage tijdelijk personeel) in subsequent models, with the final model reaching an R^2 of 0.618. These findings emphasize the critical influence of student composition and staffing conditions on target-level academic success, supported by the Durbin-Watson statistic of 2.043, indicating no autocorrelation in the residuals. The coefficients are provided in Table 10.

Table 5. School dynamics on target level achievement

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
4	(Constant)	54.277	3.940		13.776	.000	46.500	62.053					
	% beroepskader	-.359	.078	-.341	-4.608	.000	-.513	-.205	-.709	-.330	-.216	.401	2.493
	% VWO	.353	.060	.390	5.872	.000	.234	.471	.687	.407	.275	.497	2.012
	% HAVO VWO	.310	.100	.170	3.099	.002	.112	.507	.452	.229	.145	.727	1.376
	Het percentage tijdelijk personeel ten opzichte van het totale personeel	-.201	.068	-.140	-2.951	.004	-.336	-.067	-.227	-.218	-.138	.980	1.020

a. Dependent Variable: Streefniveau

The coefficients presented in the final model highlight the significant contributions of school-level variables to target-level academic achievement. The percentage of students in vocational education with the lowest academic level (*% beroepskader*) is a strong negative predictor (*B = -0.359, β = -0.341, p < 0.001*), indicating that a higher proportion of such students is associated with lower academic achievement. Conversely, the percentage of students in pre-university tracks (*% VWO*) is the strongest positive predictor (*B = 0.353, β = 0.390, p < 0.001*), suggesting that schools with a higher proportion of students in these tracks achieve better outcomes. The percentage of students in combined higher academic tracks (*% HAVO/VWO*) also positively influences achievement (*B = 0.310, β = 0.170, p = 0.002*). Additionally, the percentage of temporary staff (*Het percentage tijdelijk personeel*) negatively impacts achievement (*B = -0.201, β = -0.140, p = 0.004*), reflecting the potential challenges posed by staffing instability. These findings underscore the critical roles of student composition and staff conditions in shaping target-level academic success, with the model providing robust explanatory power as reflected by the acceptable tolerance and VIF values.

4.2.3. Bridging Neighborhoods and Schools: A Hierarchical Analysis of Target-Level Academic Achievement

In this section, hierarchical regression analysis was conducted to explore the relationship between target-level academic achievement and the statistically significant neighborhood and school indicators identified in the stepwise regression analysis. The model summary is presented in Table 11.

Table 6. Neighborhood and school effects on target level model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.576[a]	.332	.321	12.2765	.332	29.018	3	175	.000	
2	.794[b]	.630	.615	9.2385	.298	34.504	4	171	.000	2.068

The hierarchical regression analysis results, summarized in Table 11, reveal that the combined influence of neighborhood and school-level factors significantly predicts target-level academic achievement, explaining 63% of the variance in the final model ($R^2 = 0.630$, $p < 0.001$). In the first model, neighborhood-level predictors, including the proportion of non-Western migrants, population density, and average income, accounted for 33.2% of the variance ($R^2 = 0.332$, $p < 0.001$). The addition of school-level variables in the second model, including the percentage of temporary staff, students in pre-university tracks (% VWO), combined higher academic tracks (% HAVO/VWO), and vocational tracks with the lowest academic level (% beroepskader), significantly improved the explanatory power by 29.8% (R^2 change = 0.298, $p < 0.001$). The Durbin-Watson statistic of 2.068 indicates no autocorrelation in the residuals, confirming the robustness of the model. The coefficients of the analysis is provided in Table 12.

Table 7. Hierarchical neighborhood analysis on target level achievement coefficients

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	46.628	6.368		7.322	.000	34.060	59.196					
	Gemiddeld inkomen per inwoner	.000	.000	.344	3.761	.000	.000	.001	.528	.273	.232	.457	2.189
	Dichtheid per km2 van bevolking	.000	.000	.162	2.599	.010	.000	.001	.221	.193	.161	.986	1.014
	Het aandeel migranten in de totale bevolking (Non-westers)	-.180	.072	-.229	-2.500	.013	-.322	-.038	-.502	-.186	-.154	.454	2.201
2	(Constant)	52.712	6.157		8.561	.000	40.558	64.865					
	Gemiddeld inkomen per inwoner	3.401E-5	.000	.032	.424	.672	.000	.000	.528	.032	.020	.381	2.625
	Dichtheid per km2 van bevolking	.000	.000	.080	1.661	.099	.000	.000	.221	.126	.077	.928	1.077
	Het aandeel migranten in de totale bevolking (Non-westers)	-.056	.056	-.072	-1.011	.313	-.166	.054	-.502	-.077	-.047	.428	2.337
	% beroepskader	-.308	.080	-.293	-3.839	.000	-.467	-.150	-.709	-.282	-.178	.372	2.690
	% VWO	.326	.065	.361	5.037	.000	.199	.454	.687	.359	.234	.421	2.378
	% HAVO VWO	.301	.101	.166	2.994	.003	.103	.500	.452	.223	.139	.706	1.416
	Het percentage tijdelijk personeel ten opzichte van het totale personeel	-.187	.069	-.129	-2.716	.007	-.322	-.051	-.227	-.203	-.126	.954	1.049

a. Dependent Variable: Streefniveau

The coefficients from the hierarchical regression analysis illustrate the significant contributions of both neighborhood and school-level variables to target-level academic achievement. In the first model, neighborhood-level factors such as average income (*$B = 0.000$, $\beta = 0.344$, $p < 0.001$*), population density (*$B = 0.000$, $\beta = 0.162$, $p = 0.010$*), and the proportion of non-Western migrants (*$B = -0.180$, $\beta = -0.229$, $p = 0.013$*) were significant predictors. However, their influence diminished in the second model with the addition of school-level variables.

In the final model, key school-level variables emerged as significant predictors. The percentage of students in vocational tracks with the lowest academic level (*% beroepskader*) had a strong negative effect (*$B = -0.308$, $\beta = -0.293$, $p < 0.001$*), while the percentage of students in pre-university tracks (*% VWO*) had the most substantial positive impact (*$B = 0.326$, $\beta = 0.361$, $p < 0.001$*). The percentage of students in combined higher academic tracks (*% HAVO/VWO*) also positively influenced target-level achievement (*$B = 0.301$, $\beta = 0.166$, $p = 0.003$*). Additionally, the percentage of temporary staff negatively affected outcomes (*$B = -0.187$, $\beta = -0.129$, $p = 0.007$*), reflecting the challenges associated with staffing instability.

Overall, these findings emphasize that while neighborhood characteristics initially play a significant role, their effects are largely mediated through school-level factors. This underscores the importance of addressing school dynamics, such as student composition and staffing conditions, to effectively mitigate the influence of broader socioeconomic and demographic disparities on academic achievement.

4.2. Visualization on Map

This section maps schools with the highest and lowest academic achievement to visualize their geographic distribution. The locations of these schools are presented in Figure 1.

Figure 1. Visualization of higher and lower scoring schools on map: This visualization includes schools with a target achievement level above 80% and below 30%, highlighting the extreme ends of academic performance within the dataset

In Figure 1, schools with the highest academic performance are indicated by white markers within blue circles, while green flags represent schools with the lowest academic performance. The distribution on the map reveals that schools with high academic performance are clustered in specific areas, whereas schools with low academic performance are concentrated in distinct regions. This visualization suggests that proximity to the city center may be an essential factor in explaining differences in school performance in Amsterdam, as schools with higher academic achievement tend to cluster closer to the center, while lower-performing schools are more often located farther away.

5. Discussion

The findings of this study provide critical insights into the intersection of neighborhood and school-level factors in shaping academic achievement, aligning with and expanding upon the existing body of research.

Consistent with earlier studies (e.g., Bauder, 2001; Kauppinen, 2007), our results underscore the significant role of neighborhood socio-economic conditions, particularly average income levels, in influencing academic outcomes. Higher neighborhood income was found to positively predict both fundamental and target-level academic success, supporting the notion that wealthier neighborhoods provide better access to educational resources and skilled teachers. Similarly, the positive influence of population density on academic outcomes may reflect the enhanced access to urban infrastructures such as libraries, extracurricular programs, and community networks in densely populated areas, as highlighted by Zorlu and Latten (2009). However, in addition to Zorlu and Latten's findings, this study identifies that impoverished and immigrant groups are increasingly pushed to the urban periphery, leading to a decline in academic achievement as one moves farther from Amsterdam's city center.

These findings echo broader literature on spatial inequality in educational access, particularly in relation to residential filtering processes shaped by housing markets and school catchment policies. As Francis and Hutchings (2013) argue, property values function as socioeconomic filters restricting low-income families from accessing high-performing schools. This dynamic is reinforced by school enrollment zones, which often codify residential advantage into educational privilege (Hamnett & Butler, 2011). Our data showing higher academic achievement in wealthier neighborhoods may, therefore, not only reflect resource access but also systemic exclusion mechanisms that limit mobility for disadvantaged students.

However, the diminishing significance of neighborhood indicators, such as the proportion of non-Western migrants, in the hierarchical regression models mirrors findings from Sykes (2011), who noted that school-level socioeconomic composition often mediates the effects of neighborhood ethnicity. Our study corroborates this by showing that school-level factors, particularly student composition (e.g., beroepskader, VWO, HAVO/VWO), play a stronger role in predicting academic outcomes than neighborhood demographics. This mediating role of schools also aligns with Dietz's (2002) conceptualization of neighborhood effects as operating through contextual, endogenous, and correlational mechanisms. While neighborhood ethnicity appears as a predictor in the initial models, its diminishing significance in hierarchical models underscores how its effects are primarily channeled through institutional mechanisms within schools. In this regard, school-level factors may act as buffers or amplifiers of neighborhood disadvantage, depending on their capacity to support students across varied socio-economic backgrounds.

The negative impact of having more students who have the potential to pursue lower-level vocational education on both fundamental and target-level achievement aligns with Lupton's (2005) argument that schools serving lower-performing student populations face compounded challenges due to socio-economic barriers. Conversely, the strong positive influence of having more students with a potential to continue higher academic achieving schools reflects Kuyvenhoven and Boterman's (2021) findings that access to academically rigorous tracks is a key determinant of educational success, particularly for students in affluent neighborhoods. In light of these dynamics, the role of spatial segregation and educational tracking becomes more salient. Karsten et al. (2006) and Oberti (2007) emphasize that urban segregation—whether based on ethnicity, income, or educational background—tends to concentrate disadvantage and exacerbate inequalities across generations. The strong predictive power of student composition variables in our models, particularly the proportion of students in lower vocational tracks, can be seen as a direct consequence of such segregation patterns, where students from underprivileged neighborhoods are systematically overrepresented in less academically demanding pathways.

Staffing conditions, such as the percentage of temporary staff, also emerged as significant predictors, echoing concerns raised in prior research (e.g., Sampson et al., 2002) regarding the destabilizing effects of staffing instability on educational quality. This highlights the dual importance of institutional capacity and socio-economic contexts in shaping outcomes. The issue of staffing instability, particularly in schools serving vulnerable populations, may also be tied to broader urban inequalities. Pinkster (2007) argues that low-income neighborhoods often rely on tight-knit but opportunity-limited social networks, which may impede institutional recruitment and retention. As our data suggests, these constrained environments may contribute to higher staff turnover and an overreliance on temporary personnel—both of which negatively impact student performance. Addressing staffing inequities thus requires not only school-level interventions but also neighborhood-level strategies to enhance institutional attractiveness and sustainability.

Our findings also resonate with broader discussions on urbanization and its role in perpetuating educational inequities. Similar to Massey and Fischer (2006), we observed that urban socio-economic segregation continues to influence educational trajectories, albeit indirectly, through school composition and resource allocation. This aligns with Wilson's (2012) concept of concentrated poverty, emphasizing that neighborhood-level disadvantages are often perpetuated through systemic school-level disparities. Moreover, patterns of urban expansion and displacement appear to exacerbate educational stratification. Findings from this study—showing a decline in achievement among schools located in peripheral neighborhoods—align with research on gentrification and forced relocation (Forster, 2006; Uitermark, 2003). These processes often push low-income and immigrant families to the urban margins, where public services, including schools, are less robust. Such spatial marginalization may undermine educational continuity and limit access to quality schooling, further entrenching disadvantage among displaced populations.

Overall, this study builds on existing research by demonstrating the mediating role of school-level factors in the relationship between neighborhood characteristics and academic achievement. While neighborhood socioeconomic conditions provide the initial context for disparities, their influence is largely channeled through schools, reinforcing the importance of addressing inequities in student composition and staffing to mitigate broader spatial and economic inequalities. These findings suggest that educational policies must adopt a dual focus, addressing both the socio-economic contexts of neighborhoods and the internal dynamics of schools to achieve meaningful and sustainable improvements in academic outcomes. While this study focuses on the Dutch context, the findings also resonate with global patterns of spatial inequality. According to the United Nations (2016), unregulated urban growth and socio-spatial fragmentation are among the leading drivers of educational inequity in rapidly urbanizing regions. The mechanisms identified in our analysis—such as school composition mediating neighborhood disadvantage—highlight the universal nature of spatial determinants in education. Future research may benefit from comparative approaches that explore how different urban governance models shape these dynamics across contexts.

6. Conclusion

This study provides a comprehensive analysis of the factors influencing academic achievement at both fundamental and target levels, emphasizing the interplay between neighborhood and school-level characteristics. The findings demonstrate that while neighborhood socio-economic conditions, such as income and population density, initially play a significant role in shaping educational

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outcomes, their effects are largely mediated through school-level factors, including student composition and staffing conditions.

The results reveal a clear pattern of homogenization in student composition across schools. Some schools concentrate on academically successful students, as indicated by the positive impact of the percentage of students in pre-university tracks (VWO) and combined higher academic tracks (HAVO/VWO) on achievement, while others predominantly serve students with lower academic performance, reflected in the strong adverse effect of the percentage of students in vocational education with the lowest academic level. This polarization highlights the influence of socio-economic and demographic factors in creating a segregated educational landscape, where academic success is clustered in specific schools, leaving others with concentrated challenges. Addressing this imbalance requires targeted policies to promote more equitable student distribution and provide additional support to schools serving disadvantaged populations.

Additionally, specific neighborhood indicators, such as housing sales prices and the proportion of individuals satisfied with their health, were excluded from the study due to high correlations with income levels. This strong correlation likely reflects underlying gentrification dynamics in urban areas, where wealthier neighborhoods with higher property values attract residents with better health perceptions. These patterns emphasize the role of gentrification in reshaping urban spaces and its indirect impact on educational outcomes through neighborhood composition.

As a result, this study highlights the interconnected nature of spatial and institutional dynamics in shaping educational success. Policymakers must adopt a dual focus, addressing socio-economic disparities at both the neighborhood and school levels, to create a more equitable educational system. Future research should explore the long-term implications of these dynamics and evaluate interventions aimed at reducing segregation and supporting schools in disadvantaged areas.

6. Suggestions

Several actions are recommended to address the disparities in academic achievement and socio-spatial dynamics observed in this study. First, qualitative research focusing on individual schools is crucial to understanding the internal dynamics, such as teacher-student interactions and resource allocation, that contribute to differences in performance. The findings also highlight the gentrification process in Amsterdam, where low-income families are increasingly pushed to peripheral areas, reinforcing educational inequalities. To counteract this, social housing should be distributed more evenly across neighborhoods to maintain socio-economic diversity and ensure equal access to quality schools. Additionally, given that schools often draw students from multiple surrounding areas due to the proximity of neighborhoods, studies conducted at the wijk (district) level are necessary to capture the broader interactions influencing school performance. Finally, targeted policies are needed to balance student distribution across schools, preventing the clustering of high- and low-performing students in specific institutions and ensuring equitable opportunities for all. These measures collectively aim to create a more inclusive and equitable educational landscape in Amsterdam.

Declarations

Author Contributions. Orhun Kaptan.: Literature review, conceptualization, methodology, data collection, and data analysis. İbrahim Kocabaş.: Review-editing, original manuscript preparation, and writing. Both authors have read and approved the final version of the article.

Conflicts of Interest. The authors declare no conflict of interest.

Ethical Approval. This study utilized publicly available data and did not involve human participants. Therefore, ethical approval from an ethics committee was not required.

Data Availability Statement. The data supporting the findings of this study are available from the corresponding author, Orhun Kaptan, upon reasonable request.

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