WHO BENEFITS FROM INTELLIGENT TUTORING SYSTEMS? STATISTICAL EVIDENCE OF THE DIGITAL DIVIDE IN AUSTRALIAN HIGH SCHOOL MATHEMATICS EDUCATION

Brody Hannan

Southampton Education School, University of Southampton, brody.hannan@soton.ac.uk

Intelligent Tutoring Systems (ITS) are often promoted as equitable tools for personalised learning, yet little is known about whether they truly meet this aim, especially within the Australian schooling context. This study uses Multilevel Structural Equation Modelling (MSEM) to examine the effect of school socioeconomic status (SES) on student mathematics learning outcomes, and the extent to which student usage of an ITS platform alters this relationship. Using activity log data from the AdaptiveMath ITS platform and school-level data from the MySchool database, the analytic sample comprised of 17,633 Australian high school students (Years 7–10) across 152 schools. Results show positive, significant direct and indirect effects of school SES on student mathematics learning outcomes, through student ITS usage. Further, while student ITS usage was positively associated with mathematics learning outcomes, this relationship was stronger in high-SES schools.

Keywords: Intelligent Tutoring Systems, Socioeconomic Inequality, Digital Divide, Educational Inequality, Mathematics Education

BACKGROUND

ITS Effectiveness

Intelligent Tutoring Systems (ITS) use artificial intelligence to diagnose student understanding and deliver seemingly personalised instruction (Kulik & Fletcher, 2016). ITS platforms are particularly relevant to mathematics education, where ITS features such as adaptive sequencing, scaffolding, immediate feedback, and targeted practice can help to improve student conceptual understanding, and problem-solving (Borchers, Fleischer, Schanze, Scheiter, & Aleven, 2025). Despite the broad pedagogical and theoretical support for ITS platforms however, meta-analyses on the effectiveness of ITS platforms across various student populations and subject areas have been inconclusive (Kulik & Fletcher, 2016; Ma, Adesope, Nesbit, & Liu, 2014).

A growing line of inquiry explores ITS platforms as tools of promoting equity in low SES environments; that is, reducing achievement gaps between students from different socioeconomic backgrounds. However, these studies have not been without significant limitations. Chevalère et al. (2022), for example, found improved learning for low SES-students when using an ITS platform, however used a limited sample of students (n = 806), in a variety of non-mathematics subjects, and for a period of only 10 weeks. Muralidharan, Singh, and Ganimian (2019) found improved mathematics scores in an after-school ITS program for low SES students in rural India, however failed to account for increased instructional time, when purporting the effectiveness of the platform.

Despite these findings, ITS adoption has grown in Australian schools due to policy support for digital learning (ACARA, 2020a) and widespread student laptop access (Zagami, 2022), and continues to be promoted as a tool to narrow the Digital Divide (Stephens & Loble, 2024).

The Digital Divide

The Digital Divide comprises of disparities in (i) access, (ii) skills and use, and (iii) the benefits derived from digital use (Van Deursen & Van Dijk, 2013). These levels often mirror and reinforce existing, offline inequalities (Van Deursen & Helsper, 2015). For example, Rafalow (2020)'s ethnography of American high schools found digital technology use to vary by school-level SES, where affluent schools encouraged creative use of technology, while lower-income schools emphasised routine compliance. Within the ITS context, Hannan and Eynon (2025) found an Australian ITS platform to partially mediate the effect of school SES on student mathematics learning outcomes.

The Present Study

This study uses MSEM to examine direct and indirect effects of school SES on student mathematics learning outcomes, through student usage of the AdaptiveMath ITS platform. The present study moves beyond Hannan and Eynon (2025)'s prior analysis by considering a multilevel approach (students nested within classes nested within schools, Figure 1), while seeking to validate results using an updated 2024 dataset, as well as national standardised testing to measure learning outcomes, in addition to those used internally by the ITS platform.

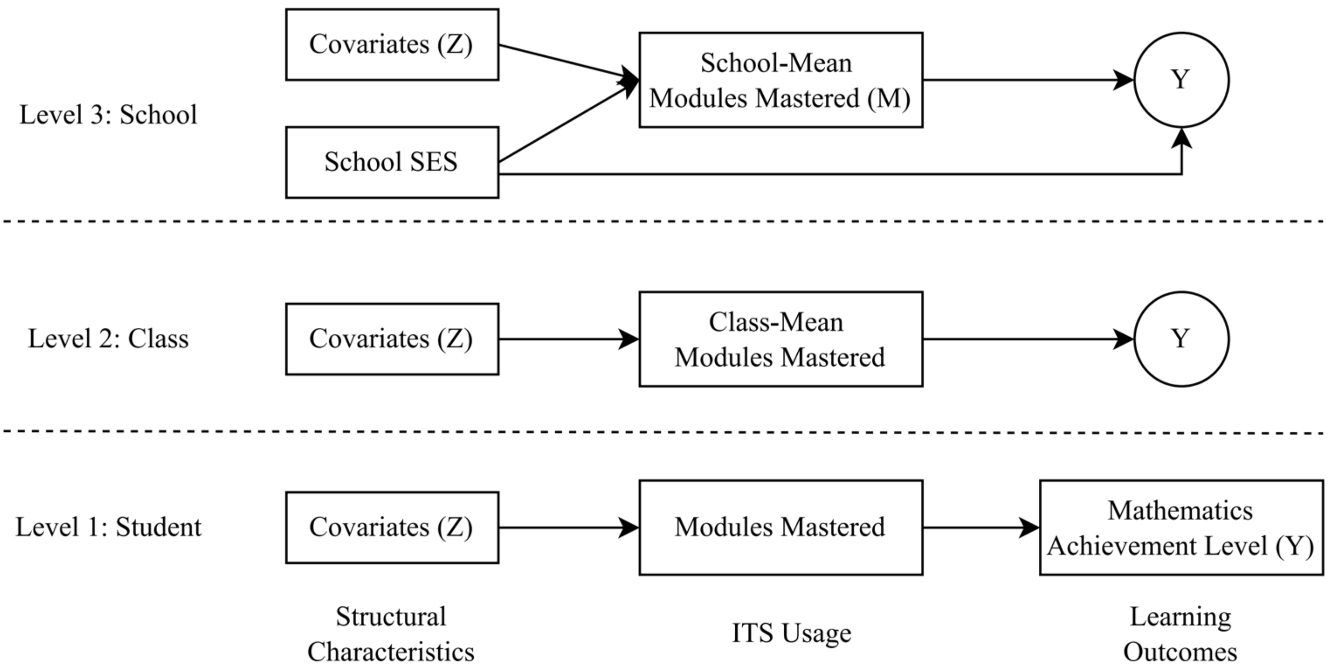

Figure 1. Proposed MSEM Conceptual Model

Note: Multilevel Structural Equation Model (MSEM) conceptual framework, adapted from Hannan and Eynon (2025)'s earlier SEM. The diagram is structured across three nested levels: students within classes, within schools. At Level 1 (student), structural characteristics (e.g., experience with the platform, year level, prior achievement) predict ITS usage, measured as modules mastered, which in turn predicts mathematics achievement outcomes. At Level 2 (class), student variables are aggregated (e.g., class-mean modules mastered), allowing examination of classroom-level effects. At Level 3 (school), school socio-educational advantage and other school-level covariates predict school-mean modules mastered, which in turn predicts aggregated mathematics achievement. The outcome variable (Y; mathematics achievement level) is specified at each level to capture within-, between-class, and between-school variance.

This study aims to address the following research question: what are the direct and indirect effects of school SES on student mathematics learning outcomes, through student usage of the ITS platform AdaptiveMath, in Australian high schools? This study hypothesises a positive direct and indirect effects between school SES and student mathematics learning outcomes through student usage of AdaptiveMath, reflecting the third level of the Digital Divide (Van Deursen & Helsper, 2015).

METHODOLOGY

Database

This study draws on two primary sources: student interaction logs from the *AdaptiveMath* ITS platform and school-level data from the MySchool database (ACARA, 2022). The *AdaptiveMath* logs capture student engagement and performance over time. The MySchool platform provides demographic and performance data for all Australian schools. Datasets were merged using school name as a common identifier. The resulting dataset included 21,421 students from 1,516 classes across 216 schools using AdaptiveMath in 2024.

Analytic Sample

To align with the study's focus on secondary education, only students in Years 7–10 were included. Missing data were minimal, with the only variable affected being school attendance rate (0.7% of students; 0.02% of schools). These were addressed using multiple imputation (Graham, 2009). The final analytic sample comprised 17,633 students, nested within 1,229 classes across 152 schools.

Measures

Three categories of variables were used: (i) structural characteristics, (ii) student ITS usage metrics, and (iii) student mathematics learning outcomes. Students were nested within classes and within schools using unique identifications. All variables yielded Variance Inflation Factor (VIF) scores below the commonly accepted threshold of 10, and tolerance values exceeded 0.1, indicating that multicollinearity was not a concern (Kline, 2023). To address any violations of normality in the data, the analysis employed Maximum Likelihood Robust (MLR) estimation (Kline, 2023).

Structural Characteristics

*Experience with AdaptiveMath***.** Prior experience with AdaptiveMath, measured as the number of years used before 2024 (M = 1.03, SD = 1.07).

Socioeducational Advantage. School SES was measured using ACARA's 'index of community socioeducational advantage' (ICSEA) percentile score (ACARA, 2020b) (M = 60.66, SD = 20.59, Min = 0, Max = 97). This measure has been widely adopted in Australian education research addressing structural inequality and school performance (Riddle, 2018) since its introduction in 2012.

Class Size. Calculated from the number of students sharing a unique class ID (M = 19.44, SD = 6.95).

Attendance Rate. The Semester 1 attendance rate for each school (M = 88.00, SD = 3.37).

Year Level. The student's year level in school, used as a proxy for age (M = 7.83, SD = 0.85).

Location. The school's location, categorised to be consistent with the Australian Bureau of Statistics, dummy coded into Inner Regional (29%), Outer Regional (12.6%) and Remote or Very Remote (0.6%), compared against Major Cities (56.8%).

ITS Usage Metrics

Modules Mastered. The total number of modules a student mastered in 2024 (M = 43.57, SD = 21.89). Mastery is determined in the AdaptiveMath platform through fortnightly review tests of prior modules completed and used as a proxy for ITS usage, given the absence of behavioural tracking data.

Learning Outcome Metrics

Achievement Level. Internal achievement metric used in AdaptiveMath, aligned to the Australian curriculum, ranging from 0 (pre-Year 1) to 11 (Year 10 completion). Measured at both the beginning (M = 4.54, SD = 1.48) and end (M = 6.2, 1.41) of the 2024 academic year.

NAPLAN. The results of the numeracy domain of Australia's national standardised testing assessment, occurring every 2 years (Year 7 and 9) within the analytic sample. NAPLAN uses a common scale ranging from 0 to 1000 (M = 545.11, SD = 27.53), allowing for achievement scores to be compared across year levels within the analytic sample.

DATA ANALYSIS

This study uses MSEM to examine direct and indirect effects of school SES on student mathematics learning outcomes, through student usage of the *AdaptiveMath* ITS platform. MSEM extends traditional Structural Equation Modelling (SEM) by simultaneously estimating within- and between-group variance structures, making it particularly suited to nested data in educational contexts (Hall, Malmberg, Lindorff, Baumann, & Sammons, 2020). In Australian research, MSEM has previously been used to model the effects of SES composition (Sciffer, Perry, & McConney, 2022).

This study estimated three sequential MSEM models:

Model 1 replicated Hannan and Eynon (2025)'s analysis using updated AdaptiveMath 2024 data, and a multilevel structure. Model 1 examined the direct and indirect effects of school SES on student mathematics learning outcomes through the number of modules students mastered on the AdaptiveMath platform.

Model 2 used a subset of the analytic sample (N = 10,827) comprising of only Year 7 and Year 9 students, enabling direct comparison with students who also completed the NAPLAN numeracy assessment the same year.

Model 3 retained the same analytic sample as Model 2, but replaced the internal AdaptiveMath End Achievement Level variable with class aggregated NAPLAN Numeracy scores, to examine whether findings generalised to a nationwide, standardised assessment.

RESULTS

Intraclass Correlation Coefficient (ICC)

Intraclass Correlation Coefficients (ICCs) revealed a non-trivial proportion of variance in student achievement was attributable to clustering at the student (within) level (ICC = 0.450), classroom level (ICC = 0.201) and the school level (ICC = 0.349), confirming the appropriateness of a three-level MSEM for the analysis.

Model Fit

Model fit indices such as the CFI, TLI, and RMSEA could not be computed due to model saturation. However, the model structure of the present study is a multilevel extension of the conceptual model presented by Hannan and Eynon (2025), which demonstrated excellent model fit using conventional absolute model fit criteria. While absolute model fit indices are widely used, Kenny, Kaniskan, and McCoach (2015) argue they are not definitive indicators of validity, especially in complex multilevel models with low degrees of freedom.

Predictors of Mathematics Achievement

A summary of key results is displayed in Table 1. For example, at the within-student level, modules mastered positively and significantly predicted end-of-year mathematics achievement, such that one additional module mastered predicted a student to be 0.014 'years ahead' in their mathematics achievement level by the end of 2024 (b = 0.014, p < .001). Pathways with covariates (not featured in Table 1), indicated students who started at higher achievement levels mastered more modules (b = 4.620, p < .001), while older students mastered fewer modules (b = -8.083, p < .001). At the school level, school-mean modules mastered significantly predicted student end-of-year achievement (b = 0.015, p < .001), whereas school SEA was not statistically significant (b = 0.004, p = .110), but did positively predict school-mean modules mastered (b = 0.162, p < .01).

		Model 1	**Model 2**	**Model 3**
	Pathway	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**
Level 1 (Student)	Modules Mastered -> End Achievement Level	0.014 (0.001)***	0.017 (0.001)***	
Level 2 (Class)	Modules Mastered -> End Achievement Level	-0.005 (-2.489)*	-0.023 (0.003)***	
	Modules Mastered -> NAPLAN			-0.454 (0.065)***
Level 3 (School)	Modules Mastered -> End Achievement Level	0.015 (3.593)***	0.023 (0.005)***	
	Modules Mastered -> NAPLAN			0.582 (0.121)***
	School SEA -> End Achievement Level	0.004 (0.002)	0.002 (0.003)	
	School SEA -> NAPLAN			0.871 (0.083) ***
	School SEA -> Modules Mastered	0.162 (0.063)**	0.097 (0.084)	0.006 (0.005)

Table 1. Summary of key results of MSEM Across Models 1, 2 and 3

Note: Unstandardised estimates. * = p < 0.05, ** = p < 0.01, *** p < 0.001. SEA = Socioeducational advantage. Each level relates to respective level aggregate. For example, Modules Mastered -> End Achievement Level at the School Level relates to the School Mean Modules Mastered, and its relationship to the School Mean Achievement Level. Model 3 does not contain any results at the Student Level as the NAPLAN score is only a class-aggregate.

Surprisingly, the findings of Models 2 and 3 yielded statistically insignificant results for school socioeducational advantage's relationship to modules mastered. For example, in Model 3, while both school-mean modules mastered and school socioeducational advantage were found to have a positive, statistically significant effect on NAPLAN results, a similar relationship was not found between school socioeducational advantage and school-mean modules mastered, indicating an absence of an indirect effect.

Further analysis was then conducted by partitioning the analytic sample into quartiles of socioeducational advantage, to examine whether schools had differing relationships between school-mean modules mastered and student mathematics learning outcomes, based upon their SES. These results are summarised below in Table 2.

	Pathway: Modules Mastered ->	School SEA Q1 (N = 619)	School SEA Q2 (N = 2,164)	School SEA Q3 (N = 4,795)	School SEA Q4 (N = 3,249)
		Estimate (SE)	Estimate (SE)	Estimate (SE)	Estimate (SE)
Level 1 (Student)	End Achievement Level (Model 2)	0.021 (0.001)***	0.017 (0.001)***	0.018 (0.001)***	0.016 (0.001)***
Level 2 (Class)	End Achievement Level (Model 2)	-0.005 (0.005)	-0.021 (0.008)**	-0.030 (0.004)***	-0.028 (0.004)***
	NAPLAN (Model 3)	-0.217 (0.207)	-0.465 (0.078)***	-0.562 (0.115)***	-0.456 (0.065)***
Level 3 (School)	End Achievement Level (Model 2)	0.005 (0.015)	0.03 (0.013)*	0.029 (0.007)***	0.027 (0.005)***
	NAPLAN (Model 3)	0.743 (0.177)	0.401 (0.118) ***	0.555 (0.194)**	0.778 (0.159)***

Table 2. Summary of key results of MSEM Across Models 2 and 3

Note: Unstandardised estimates. * = $p < 0.05$, ** = $p < 0.01$, *** $p < 0.001$. SEA = Socioeducational advantage. Q1 = Quartile 1. Each level relates to respective level aggregate. For example, Modules Mastered -> End Achievement Level at the School Level relates to the School Mean Modules Mastered, and its relationship to the School Mean Achievement Level. Model 3 does not contain any results at the Student Level as the NAPLAN score is only a class-aggregate.

DISCUSSION

This study examined the direct and indirect effects of school SES on student mathematics learning outcomes, through student usage of the AdaptiveMath ITS platform. It should be noted that the explanatory power of such quantitative approaches are limited. For example, the MSEM featured in this study captures only student responses within the platform, omitting factors such as time on task, knowledge retention, or learning done outside the ITS platform. Findings should therefore be interpreted as patterns in ITS usage and achievement within the platform, not a comprehensive account of student learning.

Findings from Model 1 replicate and extend those of Hannan and Eynon (2025); demonstrating positive direct and indirect effects of school SES on student mathematics learning outcomes through student ITS usage. School SES also had a significant positive effect on the Modules Mastered variable, a proxy for student ITS usage. Using updated 2024 data and MSEM methods, these results provide empirical evidence that differences in student ITS usage may partly explain SES-related disparities in learning outcomes, whereby students in higher-SES schools may have higher mathematics learning outcomes because they use the ITS platform more effectively.

Models 2 and 3, limited to Year 7 and 9 subsamples, did not replicate these effects. Stratifying by year group weakened or eliminated the SES–ITS–achievement relationship, suggesting that the effect of school SES on student ITS usage or mathematics learning outcomes is not consistent across student cohorts.

Although Models 2 and 3 showed no school-level effects, student ITS usage consistently predicted mathematics outcomes across all models when partitioned into SES quartiles (Table 2). Positive class- and school-level associations appeared only in high-SES schools, suggesting a threshold whereby collective ITS benefits emerge only above a certain SES level. This aligns with Hall et al. (2020)'s concept of Airbag Moderation, where a moderating variable (e.g., student ITS usage) is activated by a contextual risk (e.g., low SES) and therefore dependent on the predictor variable. In practice, this suggests that ITS platforms such as AdaptiveMath may not be equally effective across school contexts, where higher SES schools appear better able to translate student ITS usage into improvements in mathematics achievement. Within mathematics education, ITS platforms should therefore be used with consideration for the school context, rather than assuming universal benefit.

Future research should explore student ITS usage patterns more closely to establish differences in student usage and learning using inductive methods. Learning analytics could be used to examine granular aspects of student engagement within the AdaptiveMath platform—such as time on task, session frequency, and indicators of student help-seeking behaviour and self regulation to understand individual typologies of student usage.

CONCLUSION

This study examined the direct and indirect effects of school SES on mathematics outcomes through student use of the AdaptiveMath ITS platform. Three MSEM analyses were conducted using both internal AdaptiveMath achievement levels and national standardised NAPLAN numeracy scores. Results found school SES effects partially mediated by ITS usage, but these patterns did not replicate when stratified by year group, suggesting non-linear or conditional effects. Additional analysis by SES quartiles showed that class- and school-level ITS usage was more strongly associated with achievement in high-SES schools, indicating a threshold effect whereby collective benefits of student ITS use depends on a minimum level of school SES.

REFERENCES

ACARA. (2020a). General Capabilities (Version 8.4). Retrieved from https://www.australiancurriculum.edu.au/f-10-curriculum/general-capabilities/

ACARA. (2020b). *Guide to understanding the Index of Community Socioeducational Advantage (ICSEA)*. Retrieved from https://www.myschool.edu.au/media/1820/guide-to-understanding-icsea-values.pdf

ACARA. (2022). My School: Canberra Grammar School. Retrieved from https://www.myschool.edu.au/school/49990

Borchers, C., Fleischer, H., Schanze, S., Scheiter, K., & Aleven, V. (2025). High scaffolding of an unfamiliar strategy improves conceptual learning but reduces enjoyment compared to low scaffolding and strategy freedom. *Computers & Education, 236*, 105364. doi:https://doi.org/10.1016/j.compedu.2025.105364

Chevalère, J., Cazenave, L., Berthon, M., Martinez, R., Mazenod, V., Borion, M.-C., . . . Huguet, P. (2022). Compensating the socioeconomic achievement gap with computer-assisted instruction. *Journal of Computer Assisted Learning, 38*(2), 366-378. doi:https://doi.org/10.1111/jcal.12616

Graham, J. W. (2009). Missing data analysis: making it work in the real world. *Annu Rev Psychol, 60*, 549-576. doi:10.1146/annurev.psych.58.110405.085530

Hall, J., Malmberg, L.-E., Lindorff, A., Baumann, N., & Sammons, P. (2020). Airbag moderation: the definition and statistical implementation of a new methodological model. *International Journal of Research & Method in Education, 43*(4), 379-394.

Hannan, B., & Eynon, R. (2025). Widening the Digital Divide: The mediating role of Intelligent Tutoring Systems in the relationship between rurality, socioeducational advantage, and mathematics learning outcomes. *Computers & Education, 233*, 105312. doi:https://doi.org/10.1016/j.compedu.2025.105312

Kenny, D. A., Kaniskan, B., & McCoach, D. B. (2015). The performance of RMSEA in models with small degrees of freedom. *Sociological Methods & Research, 44*(3), 486-507.

Kline, R. B. (2023). *Principles and practice of structural equation modeling*: Guilford publications.

Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of Intelligent Tutoring Systems: A Meta-Analytic Review. *Review of Educational Research, 86*(1), 42-78. doi:10.3102/0034654315581420

Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. *Journal of Educational Psychology, 106*(4), 901.

Muralidharan, K., Singh, A., & Ganimian, A. J. (2019). Disrupting Education? Experimental Evidence on Technology-Aided Instruction in India. *American Economic Review, 109*(4), 1426-1460. doi:10.1257/aer.20171112

Rafalow, M. H. (2020). *Digital divisions: How schools create inequality in the tech era*. Chicago: University of Chicago Press.

Riddle, S. (2018). Resisting educational inequity and the 'bracketing out' of disadvantage in contemporary schooling. In *Resisting educational inequality* (pp. 16-30): Routledge.

Sciffer, M. G., Perry, L. B., & McConney, A. (2022). The substantiveness of socioeconomic school compositional effects in Australia: measurement error and the relationship with academic composition. *Large-scale Assessments in Education, 10*(1), 21.

Stephens, K., & Loble, L. (2024). Securing digital equity in Australian education.

Van Deursen, A., & Helsper, E. J. (2015). The third-level digital divide: Who benefits most from being online? In *Communication and information technologies annual* (Vol. 10, pp. 29-52): Emerald Group Publishing Limited.

Van Deursen, A., & Van Dijk, J. (2013). The digital divide shifts to differences in usage. *New Media & Society, 16*(3), 507-526. doi:10.1177/1461444813487959

Zagami, J. (2022). *Computer education in Australian schools 2022*. Retrieved from Canberra, Australia: