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Widening the Digital Divide: The mediating role of Intelligent Tutoring Systems in the relationship between rurality, socioeducational advantage, and mathematics learning outcomes

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ABSTRACT

This study examines how the effects of school socioeducational advantage and rurality upon mathematics learning outcomes, are impacted by students' usage of the ITS platform AdaptiveMath. Activity log data from the AdaptiveMath platform was merged with school sociodemographic data from the public MySchool database. The final analytic sample comprised of 66,451 Australian high school students across 304 schools in Years 7–10, who used the AdaptiveMath ITS platform in 2023. Structural Equation Modelling was employed to examine both the direct and indirect effects of school socioeducational advantage and rurality on student usage of the AdaptiveMath platform, and the resulting student learning outcomes.

This study finds marginal, but statistically significant relationships between ITS usage and learning outcomes, and the socioeducational advantage and rurality of a student's school. Students who are from more affluent and urban schools use the ITS platform earlier in their school career, for more years, and have higher learning outcomes than their rural, less affluent peers. Further, ITS usage was found to mediate the relationship between socioeducational advantage and rurality, such that it amplified the positive effects of socioeducational advantage, and the negative effects of rurality, upon learning outcomes.

The results suggest that introducing ITS platforms into Australian mathematics teaching will not reduce achievement gaps between affluent and disadvantaged schools. Rather, a Matthew Effect may be observed, whereby students attending privileged schools use ITS platforms more effectively, thereby contributing to an even greater disparities in learning outcome.

1. Background

1.1. ITS effectiveness

Questions of ITS effectiveness upon improving learning outcomes have long existed, (Kulik & Fletcher, 2016; Ma et al., 2014), although little attention has been given to the Australian context. Notably, some studies indicate that ITS platforms can lead to significant learning gains under certain conditions, particularly for students who are already academically inclined or have access to additional support (Muralidharan et al., 2019). However, large-scale meta-analyses reveal the impact of ITS platforms upon student

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achievement is inconsistent, and often confined to specific contexts without translation to broader educational success (Kulik & Fletcher, 2016). One key inconsistency in assessing ITS effectiveness is the failure to consider how the quantity of ITS platform use mediates its efficacy. For example, Muralidharan et al. (2019) examined the effectiveness of an ITS platform in India within an after-school program. Their findings suggested that students who used the ITS platform achieved higher mathematics test scores than those who did not. However, this improvement may have been driven, at least in part, by the additional study time afforded by using the ITS platform outside of regular school hours, rather than the platform itself, and highlighting the need to account for the quantity of ITS use as a potential mediating factor when evaluating ITS platform effectiveness.

With respect to socioeconomic status (SES), it is well-established that regardless of a student's own individual SES, the SES of the school in which they attend is also related to the student's academic achievement (Chesters & Daly, 2017; Perry et al., 2022). Additionally, SES interacts and interrelates with rurality (Chesters & Cuervo, 2022; Roberts et al., 2024). For example, students who are both rural and low SES experience particularly lower learning outcomes when compared to their affluent and urban counterparts (Daniele, 2021).

Previous research has described how those of high and low affluence may use technology differently, but these works have predominantly relied upon surveys (Azubuike et al., 2021; Eynon & Malmberg, 2021) or qualitative studies (Rafalow, 2020). For example, Rafalow (2020)'s ethnography of three schools in the United States highlighted how differences in school characteristics along racial and socioeconomic lines contributed to different digital technologies being used, for differing uses, and with different learning outcomes. Rafalow (2020)'s ethnographic study further illustrates how despite having equal access to technology, the way technology is used in the classroom can vary significantly, affecting student learning outcomes. Meanwhile, Eynon and Malmberg (2021) developed a Structural Equation Model using nationally representative survey data to measure how adult users of the internet in Britain received the benefits of using the internet differently, along lines of existing socioeconomic disparities.

Other studies have considered ITS platforms and its effectiveness in improving learning outcomes for a variety of student groups. Specifically, ITS platforms have been assessed for their ability to improve learning outcomes for students of low socioeconomic backgrounds, but have only done so by exclusively measuring the change in student achievement before and after the intervention of the ITS platform, without any large-scale comparison between students of different schools (Han et al., 2019; Kulik & Fletcher, 2016). Such studies have assessed ITS platform effectiveness in low SES communities such as those in Peru (Beuermann et al., 2015), India (Muralidharan et al., 2019), rural China (Xu et al., 2019) and urban public schools in the United States (Ahn et al., 2016).

Meanwhile, studies such as Chevalère et al. (2022) have sought to compare usage of the same ITS platform across both low and high SES schools, however their methodology faced significant limitations. These included a relatively small sample size (N = 806), non-randomised assignment of control and intervention schools based upon the existing availability of personal computers within the schools, a short duration of ITS usage of only 4–10 weeks, and only recruiting schools of the most extreme categories of SES, which overlooks the full range of SES backgrounds (Chevalère et al., 2022). Large-scale metanalyses however, show inconclusive impacts on student achievement. For example, in a metanalysis of ITS effectiveness studies, Kulik and Fletcher (2016) concluded that in cases where positive effects were found as a result of ITS use, such positive learning outcomes often did not extend beyond the specific contexts of the ITS platform, and across to external, school-based standardised testing.

With respect to potential differences in how students from rural or urban schools use ITS platforms, there exists a dearth of comparative studies examining learning outcomes in mathematics. In a study of rural and suburban 4th-grade students using ITS platforms to improve reading comprehension, Wijekumar et al. (2012) found no statistically significant interactions between ITS learning outcomes and students in rural versus suburban schools. Meanwhile, Paquette and Baker (2017) examined how students' attempts to "game" a mathematics ITS platform varied across rural, suburban and urban schools, finding differences in gaming behaviour across the different learning environments. Further, Baker and Gowda (2010), analysing ITS platform data from urban, suburban, and rural schools, found that students in urban schools exhibited higher levels of off-task behaviour compared to their rural counterparts.

While these findings suggest students in schools of differing socioeconomic or geographic environments may use ITS platforms differently, the potential differences in the learning outcomes of students from differing geographic or socioeconomic environments using the same ITS platform, is not clearly understood. Specifically, while existing research from Muralidharan et al. (2019), Beuermann et al. (2015) and others (Huang et al., 2016; Khazanchi et al., 2022; Yu & Chen, 2016) have predominantly focused on low-performing, low-SES students from a single geographic region, they have not considered how SES and rurality interact and interrelate, nor have they compared the results of these students with their affluent, urban peers.

1.2. The Digital Divide

Previous research describing the Digital Divide, which attempts to describe the disparities in access, uses and benefits with regards to digital technology, is also relevant. Consisting of three levels, the second level of the Digital Divide is concerned with differences in the skills and extent by which different groups of people use available digital technology (Van Deursen & Van Dijk, 2013), with Hargittai et al. (2019) noting that physical access to technology becomes ineffectual without the requisite skills, knowledge, and support that enable effective use. The third level of the Digital Divide refers to the disparities in outcomes that people obtain from their use of digital technologies. Specifically, it seeks to explain how, despite having the same level of accessibility and skills, privileged users can be "more effective at converting [digital] access into information, and information into occupation advantage or social influence than less privileged users" (Van Dijk, 2020, p. 119).

Empirical studies further the argument that even when access and basic usage of a digital technology are equal, deeper inequities in social structures may lead to different outcomes as a result of technology use. Specifically, within the context of education, students of high socioeconomic status have been found to leverage digital technology in ways that result in even greater social and economic advantage (Ma, 2021; Van Dijk, 2020). For example, Rafalow (2020)'s ethnographic study of technology use in three schools in the United States further illustrates how despite having equal access to technology, the way technology is used in the classroom can vary significantly, affecting student learning outcomes.

1.3. The present study

This study contributes to this existing literature by simultaneously comparing both the ITS usages and learning outcomes of students from across differing socioeconomic and geographic backgrounds within the Australian context of students in Years 7–10. Additionally, this study uses a uniquely large sample size (N = 66,451), drawn from two datasets: activity log data from the AdaptiveMath ITS platform, and sociodemographic measures from the publicly available MySchool database.

This research draws upon Eynon and Malmberg (2021)'s mediation model of social characteristics and engagement with online learning to examine the impact of school socioeconomic advantage and rurality on student ITS usage and mathematics learning outcomes within Australian high schools.

Fig. 1 presents a conceptual framework modelling the theoretical relationship between social characteristics, ITS usage, and learning outcomes. Adapted from Eynon and Malmberg (2021, p. 572)'s "structure, agency, and outcomes" framework, this model positions ITS usage as a mediator of the relationship between students' social characteristics and their mathematics learning outcomes. Due to limitations in the dataset, this study uses socioeducational advantage as a proxy for socioeconomic status.

As well as school socioeducational advantage and rurality, the theoretical model (Fig. 1) also includes various student and school characteristics which have been shown to affect student learning outcomes, including student to teacher ratio (Naik et al., 2020) and student prior experience with using the digital technology (Tarigan et al., 2023).

This study aims to address the following research questions.

1. How is school socioeducational advantage and rurality related to student usage of the ITS platform AdaptiveMath, in Australian high schools?
2. How is school socioeducational advantage and rurality related to student mathematics learning outcomes within the ITS platform AdaptiveMath, in Australian high schools?
3. How does usage of the ITS platform AdaptiveMath mediate the relationship between school socioeducational advantage and rurality, to mathematics learning outcomes within AdaptiveMath, in Australian high schools?

Related to these research questions, the following was hypothesised.

H1. Socioeducational advantage positively influences ITS usage of the AdaptiveMath platform. Conversely, rurality negatively impacts ITS usage. This hypothesis draws upon Van Deursen & Van Dijk, 2019, who note how socioeconomic factors and geographic location influence access to and effective use of technology.

H2. Socioeducational advantage positively affects mathematics learning outcomes within the AdaptiveMath ITS platform, while rurality has a negative effect. This hypothesis draws upon Warschauer and Matuchniak's (2010) assertion that socioeconomic disparities and geographic location can influence how effectively students utilise technology for academic gain.

H3. Usage of the AdaptiveMath ITS platform mediates these relationships, amplifying the positive effect of socioeducational advantage on mathematics learning outcomes, and the negative effect of rurality. This hypothesis draws upon Selwyn (2016) and Mingo and Bracciale (2018) who note a potential 'Matthew Effect' of digital technology, potentially exacerbating existing social inequalities.

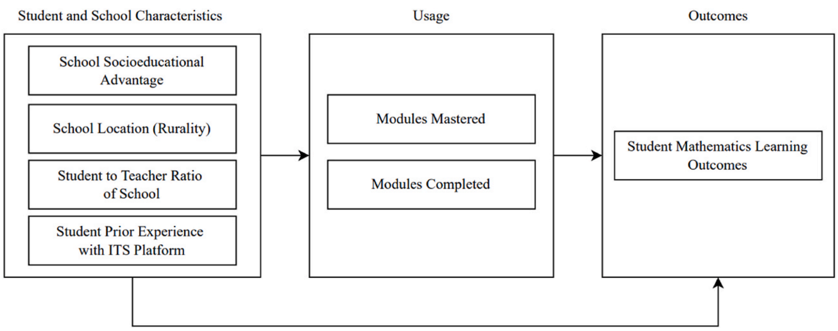

Fig. 1. Conceptual framework modelling the theoretical relationship between characteristics, ITS usage and learning outcomes.

2. Methodology

2.1. Database

This paper is based on data from two sources; raw activity log metrics from the AdaptiveMath ITS platform, and a nationally representative, public database known as MySchool (ACARA, 2020), which collects demographic data from every primary and secondary school in Australia. MySchool also features the school location and percentile of the Index of Community Socioeducational Advantage (ICSEA) values for each school.

The advantage of quantitative secondary datasets is in their tendency to use validated measurements (Smith et al., 2011), enhancing the reliability and accuracy of the findings. In the case of this study, this includes variables that measure rurality in ways that are consistent with that of the Australian Bureau of Statistics, and socioeducational advantage and achievement levels in ways that are aligned to the Australian national curriculum, and used by the Australian Curriculum, Assessment and Reporting Authority (ACARA). However, conducting a secondary data analysis on secondary datasets like MySchool presents methodological limitations, as the secondary data analysis may not reveal insights into how the data was originally constructed (Dale et al., 2008; Johnston, 2014). This is particularly relevant to the measure of socioeducational advantage, where its opaque construction as to how the variable was defined, measured or created within the original dataset may lead to misinterpretation of data and results (Johnston, 2014), therefore making the findings difficult to be compared to similar studies outside the Australian context.

2.2. Sample design

The sample drawn from the MySchool dataset consisted of a complete list of schools in Australia for the year 2023, with their school name, suburb, postcode, state or territory, ICSEA score and percentile, number of teachers and students included. The sample drawn from the AdaptiveMath user data consisted of every student user of the platform in 2023, with data as to their school, year level, number of years using AdaptiveMath, modules completed and modules mastered in 2023, as well as their overall achievement level within the platform.

The two datasets were then merged by matching school name between the MySchool and AdaptiveMath files, presenting a single dataset of 79,583 student users across 624 schools, all of whom had used AdaptiveMath in 2023.

2.3. The analytic sample

The analytic sample was selected according to the research focus of this study. First, only students in Years 7–10 were selected within the dataset, so as to focus this study only on high school students. Missingness was sparse in the analytic sample, with only 0.03 % ($N = 21$) of student entries containing datapoints unaccounted for, consisting of variables relating to school sociodemographic characteristics. All of these 21 entries with missing values were contained within a single school. Additionally, since the aforementioned school lacked only school characteristic variables, there would have been less than 50 % of sociodemographic data available, and thus unsuitable to perform multiple imputation methods (Graham, 2009).

Further, given Missing Completely at Random (MCAR) for the analytic sample ($\chi^2 = < 0.0001$, $p = 1$), the 21 student entries containing missing data were subsequently listwise deleted. Following the selection and missing data procedures, the analytic sample contained 66,451 students across 304 different schools.

2.4. Measures

Measures be featured in this study were categorised into the following: (a) structural student and school characteristics, (b) student ITS usage metrics, and (c) student learning outcome metrics.

2.4.1. Structural student and school characteristics

Returned User. Student experience using the AdaptiveMath ITS platform was measured in two ways; a Returned User dichotomous variable consisting of 0 = new user and 1 = returned user, distinguishing students who had used the AdaptiveMath platform prior to 2023. A second variable, Years Used Prior to 2023, measured the number of years a student had used the AdaptiveMath platform prior to 2023 ($M = 0.90$, $SD = 1.00$). While number of years of experience would also be valuable, this could not be included within the SEM, as preliminary analysis found the variable to not be normally distributed (skewness >1) (Cain et al., 2017). The Returned User variable was therefore selected as the measure for student experience using AdaptiveMath, with 56.1 % ($N = 37,284$) of students within the analytic sample having used the AdaptiveMath platform prior to 2023.

School Location. The rurality of the students was classified using the Remoteness Areas measure developed by the Australian Bureau of Statistics (2023). For each location, remoteness is calculated by considering the size of the local population of the region, as well as the road distance from the locality to the nearest service centre, defined as a population centre containing basic level of services such as health, education and retail (Australian Bureau of Statistics, 2023).

The original Remoteness Areas measure contained five categories. Given the small number of Very Remote students in the dataset ($N = 82$), 0.1 % of the total dataset, the Very Remote and Remote categories in the original measure were merged to classify rurality of students into four categories: Major Cities, Inner Regional, Outer regional and Remote and Very Remote. While this new category still only represented 1.2 % of the total analytic sample, it made any findings from the group to be more generalisable (Fiedler et al., 2009).

These were then dummy coded into separate variables of Major Cities, Inner Regional, Outer Regional, Remote and Very Remote. Major Cities served as the comparator.

School Socioeducational Advantage Percentile. Socioeducational advantage was used as a proxy for socioeconomic status. Socioeducational Advantage is a measure of family characteristics including parental education level and occupation, as well socio-economic background of the school's locality (ACARA, 2020). Within the analytic sample, although schools from both the lowest 0^{th} percentile and highest 99th percentile were both represented, schools in the bottom 50 percentiles of ICSEA only represented 26.7 % of the analytic sample (M = 58.26, SD = 21.2), indicating the students within the analytic sample came from predominantly more affluent schools.

While SES is commonly used in Digital Divide literature, the socioeducational advantage measure was developed by ACARA to "enable fair and meaningful comparisons between schools on the basis of the performance of their students … the combination of variables that have the strongest association with student performance" (ACARA, 2020, p. 1), namely by considering student-level parent occupation and parent education. Use of the socioeducational advantage metric has been well established in previous educational and social inequality research in Australia including Beswick et al. (2019), Chesters and Daly (2017) and Riddle (2018), since the measure was first introduced by ACARA in 2012.

Ratio of Students to Teacher. Numerous studies have identified the relevance of class size upon effective technology use in the classroom, impacting both technology use and learning outcomes. Wang and Calvano (2022) found larger class sizes tend to reduce levels of teacher interaction and student satisfaction, negatively affecting educational outcomes. Lin et al. (2019) found similar effects in digital classroom environments, where class sizes beyond 45 students had an adverse effect upon student learning outcomes. Meanwhile, increased class sizes are associated with higher levels of student off task behaviour when using technology (Zaza & Neiterman, 2019). Within the analytic sample, class size was measured as the total number of students enrolled at the school, divided by the total number of full-time equivalent (FTE) teachers at the school. Higher values indicate more students per teacher (M = 12.40, SD = 1.88).

2.4.2. Student AdaptiveMath usage metrics

ITS usage metrics can be captured through a variety of metrics, such as time spent on the platform (Karaci et al., 2018), or engagement patterns such as frequency of use, or help seeking behaviour (Aleven et al., 2016). These measures were not available for the conduct of this research. Instead, interaction with content metrics, such as Modules Completed and Modules Mastered within the AdaptiveMath platform have been utilised, aligning to similar content interaction metrics used by Ghosh (2024).

Modules Completed. This variable is a measure of how many AdaptiveMath modules a student has completed in the year 2023 (M = 57.85, SD = 32.36). To complete a module, students need to view all of the instructional material and self-declare that they have completed all the questions and viewed all the answers associated with a particular module.

Modules Mastered. This variable is a measure of how many AdaptiveMath modules a student has mastered in the year 2023. Every two weeks, all of the modules that a student has completed in the last testing cycle are re-presented to the student in the form of a test, with each test containing 2–3 questions per module. If students answer correctly all of the test questions from a particular module, the module becomes mastered, and is added to a student's achievement level. The AdaptiveMath platform approximates 40 modules mastered per year to be the standard rate of progression through the Australian national curriculum. Within the analytic sample, 55.4 % of students mastered fewer than 40 modules in 2023 (M = 38.26, SD = 24.57), indicating their rate of progression through the AdaptiveMath platform was slower than what is expected by the Australian national curriculum.

2.4.3. Student AdaptiveMath outcome metrics

Achievement Level. The AdaptiveMath platform features an Achievement Level measure, which denotes the expected level that a student would have achieved within the Australian National Curriculum, based upon all of the modules they have mastered within the AdaptiveMath platform. Within the scope of this study, this is the achievement level that a student has reached as of the end of 2023. Achievement levels are scored from 0 to 10, each denoting a year level of schooling. Within the analytic sample, student ended 2023 with achievement levels ranging from pre-Year 1 (Achievement Level = 0) to completing Year 10 (Achievement Level = 11) (M = 6.27, SD = 1.66). The achievement level that a student started the 2023 academic year with could then be calculated, by subtracting modules mastered, expressed out of 40, from the final achievement level of 2023.

Years Ahead. Is a measure of how many years ahead a student's achievement level is of their expected year level. The Years Ahead measure is calculated by subtracting a student's year level from their individual Achievement Level as calculated by the AdaptiveMath platform. Within the analytic sample, 85.6 % of students possessed an achievement level below their year level (M = −1.69, SD = 1.62).

2.5. Data analysis

This study employs Structural Equation Modelling (SEM) as the primary analytical approach due to its ability to examine multiple interdependent variables simultaneously. Given Eynon and Malmberg (2021)'s conceptual framework underpinning this research, SEM is particularly appropriate for examining both direct and indirect relationships between interdependent variables such as school location and socioeducational advantage (Suna et al., 2020), as well as AdaptiveMath usage and outcome metrics. However, it is important to acknowledge that this study relies on cross-sectional data, which limits the ability to make causal inferences (Rutkowski et al., 2024). Instead, the findings should be interpreted as associations rather than definitive causal relationships.

The statistical analyses were conducted using SPSS 29 and Mplus 8.11 software.

2.5.1. Structural Equation Modelling (SEM)

To assess multicollinearity among the predictor variables in the SEM, several diagnostic tests were conducted, with results summarised in Table 1. Variance Inflation Factor (VIF) values for all predictor variables were below the threshold of 10, while tolerance values were found to be above 0.1, suggesting no issues of multicollinearity (Kline, 2023, p. 53). Accordingly, the skewness and kurtosis values of all values were in the acceptable range of normal distribution (Kline, 2023). One exception to this was the dichotomous Returned User variable in Table 2, as skewness and kurtosis are normality measurements for continuous variables only (Cain et al., 2017).

2.5.2. Hypothesised model

A path analysis using SEM was conducted to examine the direct and indirect relationships between socioeducational advantage and rurality, and ITS usage and learning outcomes (Fig. 2).

3. Results

3.1. Preliminary data analysis

Tables 3 and 4 show how these same descriptive statistics for AdaptiveMath usage and outcome metrics vary across categories school rurality and socioeducational advantage. Students attending schools located in Major Cities, for example, mastered more modules ($M = 39.51$, $SD = 25.199$) and had an achievement score fewer years below their year level ($M = -1.564$, $SD = 1.6491$) than students attending schools in Remote and Very Remote areas ($M = 22.1$, $SD = 17.478$; $M = -2.711$, $SD = 1.8541$ respectively).

3.2. Structural model

The SEM is presented in Fig. 3 with parameter estimates contained in Table 5. The overall model fit for the structural equation model was assessed using several fit indices, and shows excellent model fit (RMSEA = 0.038, with a 90 % confidence interval of [0.033, 0.042], and a probability of RMSEA ≤0.05 of 1.000, CFI = 0.999, TLI = 0.989, SRMR = 0.013).

The model explained a large amount of the variance in the Years Ahead ($R^2 = 0.828$) and Modules Mastered ($R^2 = 0.694$) variables, however little of the variance in Modules Completed ($R^2 = 0.035$). These results indicated that the inclusion of ITS usage metrics into the model accounted for an additional 24.9 % of the variance in the Years Ahead variable. A summary of the Goodness of Fit indices and variance explained by each Model is summarised in Table 6.

3.2.1. Direct pathways to ITS usage

Research question 1 considered the relationship between school socioeducational advantage and students' ITS usage and hypothesised that higher school socioeducational advantage to be positively associated and rurality to be negatively associated, with increased ITS usage in Australian high schools. The path analysis in Fig. 3 indicates that while socioeducational advantage predicted Modules Completed and Modules Mastered in AdaptiveMath as hypothesised, rurality was not. When compared to students from Major Cities, Inner Regional Outer Regional students mastered more modules in AdaptiveMath, however students from Remote and Very Remote schools mastered fewer modules.

Specifically, socioeducational advantage was positively associated with both Modules Completed ($b = 0.243$, $\beta = 0.159$, $SE = 0.007$, $p < .001$) and Modules Mastered ($b = 0.114$, $\beta = 0.099$, $SE = 0.003$, $p < .001$) This indicates that an increase of 4.12 percentiles in a school's socioeducational advantage was associated with one additional Module Completed, and an increase of 8.77 percentiles in a school's socioeducational advantage associated with one additional Module Mastered.

3.2.2. Direct pathways to mathematics learning outcomes

Research question 2 considered how school socioeducational advantage and rurality related to learning outcomes within the AdaptiveMath platform. The direct effects contained in Fig. 3 indicate socioeducational advantage was positively associated with the Years Ahead variable, while schools located in Outer Regional, Remote and Very Remote areas were negatively associated with Years Ahead.

Specifically, increasing a school's socioeducational advantage from the 1st to 100th percentile increased the Years Ahead variable

Table 1
Tests for multicollinearity within the analytic sample.

	Tolerance	VIF
Modules Mastered	0.256	3.903
Modules Completed	0.319	3.139
Achievement Level	0.552	1.812
Years Used ITS Prior to 2023	0.324	3.085
SEA Percentile	0.647	1.546
Students Per FTE Teacher	0.809	1.237
School Location	0.773	1.294

Note. Dependent variable: Years Ahead. SEA = Socioeducational Advantage.

Table 2
Descriptive statistics of measures within analytic sample.

	Skewness	Kurtosis
Student Year Level	0.612	−0.618
Returned User[a]	−0.246	−1.939
Years of Prior ITS Use	1.008	0.691
SEA Percentile	−0.768	0.013
Students per FTE Teacher	−0.108	1.343
Usage		
Modules Mastered	0.644	0.443
Modules Completed	0.857	3.038
Learning Outcomes		
Achievement Level	0.040	2.86
Years Ahead	−0.090	0.307

Note. N = number of observations. Min = minimum. Max = maximum. M = mean. SD = standard deviation. SEA = Socioeducational Advantage. FTE = full time equivalent. [a]0 (new user) to 1 (returned user).

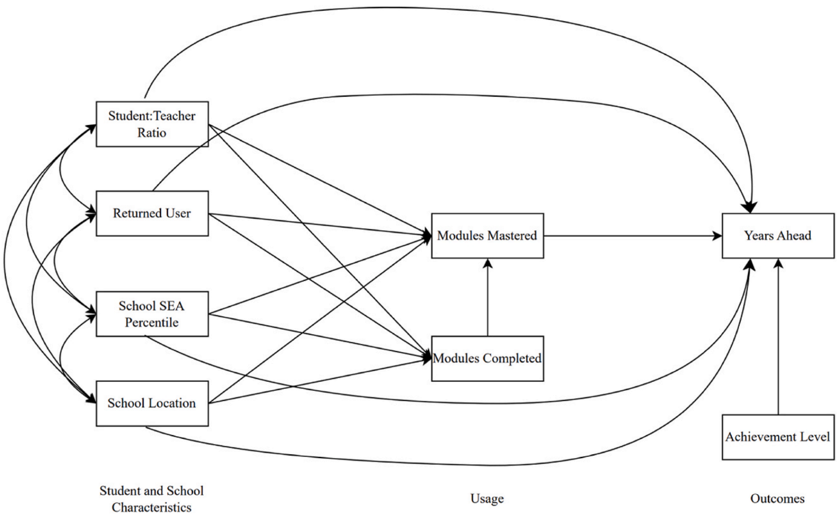

Fig. 2. Hypothesised structural equation model predicting AdaptiveMath usage and learning outcomes.

Table 3
Descriptive statistics of school and individual characteristics within analytic sample.

	N	Min	Max	M(SD)	Skewness	Kurtosis
Student Year Level	66451	7	10	7.96 (0.93)	0.612	−0.618
Returned User[a]	66451	0	1	0.56 (0.50)	−0.246	−1.939
Years of Prior ITS Use	66451	0	7	0.90(1.00)	1.008	0.691
SEA Percentile	66451	0	99	58.26 (21.20)	−0.768	0.013
Students per FTE Teacher	66451	5.72	19.11	12.40 (1.88)	−0.108	1.343

Note. N = number of observations. Min = minimum. Max = maximum. M = mean. SD = standard deviation. SEA = Socioeducational Advantage. FTE = full time equivalent.
[a] 0 (new user) to 1 (returned user).

by 0.3 (b = 0.003, β = 0.043, SE = 0.000, $p < .001$). Students from schools in Inner Regional (b = 0.032, β = 0.009, SE = 0.006, $p < .001$) areas were 0.032 further years ahead than students attending schools in Major Cities. Outer Regional (b = −0.121, β = −0.024, SE = 0.010, $p < .001$). and Remote and Very Remote (b = −0.142, β = −0.010, SE = 0.031, $p < .001$). students meanwhile were 0.121 and 0.142 years, respectively, behind students from schools located in Major Cities.

3.2.3. Relationship between ITS platform usage and learning outcomes

Research question 3 considered whether there existed a mediating relationship between ITS platform usage and predicted mathematics learning outcomes, hypothesising that ITS usage mediates the relationship between school socioeducational advantage, school rurality and mathematics learning outcomes, such that higher ITS usage leads to improved mathematics learning outcomes. The results

Table 4
Descriptive statistics of AdaptiveMath usage and outcome metrics within analytic sample.

	N	Min	Max	M(SD)	Skewness	Kurtosis
Usage						
Modules Mastered	66451	0	221	38.26 (24.57)	0.644	0.443
Modules Completed	66451	1	557	57.85 (32.36)	0.857	3.038
Learning Outcomes						
Achievement Level	66451	0	11	6.27 (1.66)	0.040	2.86
Years Ahead	66451	−9.54	4.00	−1.69 (1.62)	−0.090	0.307

Note. N = number of observations. Min = minimum. Max = maximum. M = mean. SD = standard deviation.

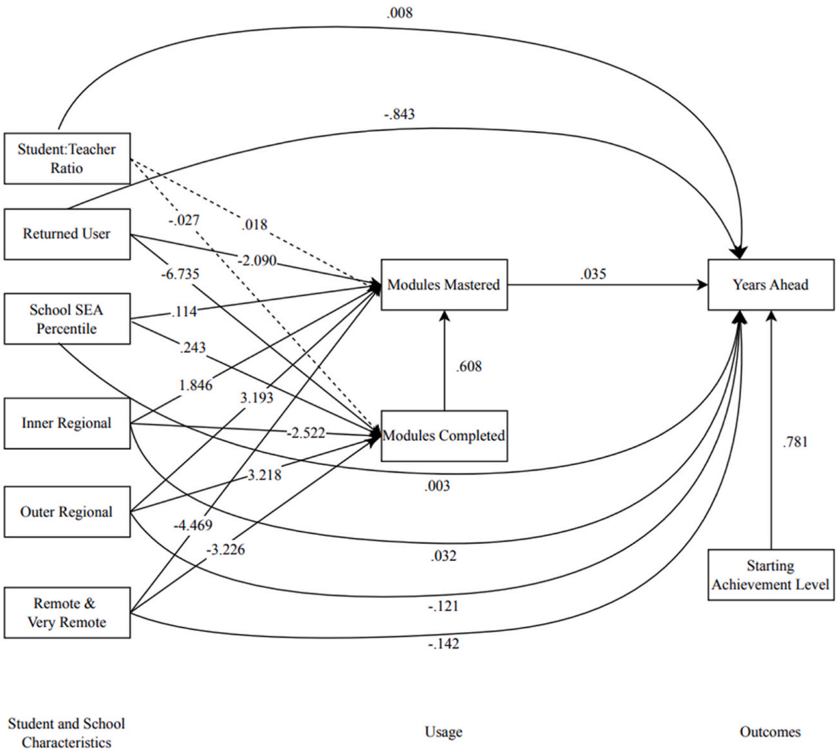

Fig. 3. Parameter estimates Structural Equation Model Predicting Usage and Outcome Metrics
Note. Values on arrows are unstandardised regression weights. Dashed lines indicate paths of non statistical-significance. SEA = socioeducational advantage. ML, $\chi^2(2) = 189.696$, $p < .001$; CFI = 0.999, TLI = 0.989; RMSEA = 0.038, 90 % CIs = [0.033, 0.042]; SRMR = 0.013.

indicate ITS platform usage had a statistically significant mediation effect on learning outcomes, where ITS usage amplified the positive effects of socioeducational advantage, and the negative effects of attending a remote and very remote school, upon student learning outcomes. As illustrated in Table 4, adding the ITS usage metrics of Modules Mastered and Modules Completed to the model increased explained variance in the Years Ahead variable, while presenting an excellent overall model fit. These findings justify the inclusion of the metrics in the model and therefore allow for a mediation analysis considering how Modules Mastered mediates the effect of school socioeducational advantage and rurality on the Years Ahead variable to be conducted.

3.3. Mediation analysis

The indirect effects of school socioeducational advantage and school location on AdaptiveMath learning outcomes were estimated using bias-corrected bootstrapped confidence intervals (CIs) (Preacher & Hayes, 2004), with 1000 bootstrap samples. Specifically, the indirect pathways from school location and socioeducational advantage percentile, to AdaptiveMath learning outcomes were measured. Standardised coefficients, standard errors, p-values, and bias corrected bootstrapped 95 % CIs for the indirect effects are presented in Table 8.

3.3.1. Indirect paths to learning outcomes through usage

The mediation analysis indicated that ITS usage is associated with the relationship between socioeducational advantage, rurality,

Table 5
Unstandardised and standardised parameter estimates for the model.

Variable	Unstandardised Estimate (SE)	Standardised Estimate (SE)	Two tailed p-value
Modules Mastered ON			
Modules Completed	0.608 (0.005)	0.804 (0.004)	<0.001
Students/FTE Teacher	0.018 (0.036)	0.001 (0.003)	0.627
Inner Regional	1.846 (0.123)	0.034 (0.002)	<0.001
Outer Regional	3.193 (0.178)	0.041 (0.002)	<0.001
Remote & Very Remote	−4.469 (0.800)	−0.020 (0.004)	<0.001
School SEA Percentile	0.114 (0.003)	0.099 (0.003)	<0.001
Returned User	−2.090 (0.127)	−0.042 (0.003)	<0.001
Starting Achievement Level	1.847 (0.046)	0.110 (0.003)	<0.001
Modules Completed ON			
Students/FTE Teacher	−0.027 (0.079)	−0.002 (0.005)	0.732
Inner Regional	−2.522 (0.282)	−0.035 (0.004)	<0.001
Outer Regional	3.218 (0.421)	0.032 (0.004)	<0.001
Remote & Very Remote	−3.226 (1.407)	−0.011 (0.005)	0.022
School SEA Percentile	0.243 (0.007)	0.159 (0.005)	<0.001
Returned User	−6.735 (0.260)	−0.103 (0.004)	<0.001
Years Ahead ON			
Modules Mastered	0.035 (0.000)	0.529 (0.002)	<0.001
Students/FTE Teacher	0.008 (0.002)	0.010 (0.002)	<0.001
Inner Regional	0.032 (0.006)	0.009 (0.002)	<0.001
Outer Regional	−0.121 (0.010)	−0.024 (0.002)	<0.001
School SEA Percentile	0.003 (0.000)	0.043 (0.002)	<0.001
Returned User	−0.843 (0.006)	−0.262 (0.002)	<0.001
Starting Achievement Level	0.781 (0.002)	0.713 (0.002)	<0.001
Remote & Very Remote	−0.142 (0.031)	−0.010 (0.002)	<0.001

Note. SE = Standard Error. SEA = Socioeducational Advantage, FTE = Full time Equivalent.

Table 6
Summary of model fit and explained variance.

Parameter	Model
Loglikelihood	
H0 Value	−658,510.854
H1 Value	−658,416.005
-2LL	1,316,832.01
Information Criteria	
Akaike (AIC)	1,317,077.707
Bayesian (BIC)	1,317,332.625
Sample-Size Adjusted BIC	1,317,243.641
Chi-Square Test of Model Fit	
Value	189.696
Degrees of Freedom	2
P-Value	0
RMSEA	
Estimate	0.038
90 Percent C.I.	[0.033, 0.042]
Probability RMSEA ≤0.05	1
CFI/TLI	
CFI	0.999
TLI	0.989
SRMR Value	0.013
Variance Explained (R^2)	
Years Ahead	0.828
Modules Mastered	0.694
Modules Completed	0.035

Note. RMSEA = Root Mean Square Error of Approximation. SRMR = Standardized Root Mean Square Residual.

and mathematics learning outcomes within the AdaptiveMath platform. However, given the cross-sectional nature of the data, these findings should be interpreted as correlational rather than causal. Specifically, socioeducational advantage (SEA) percentile had a significant positive indirect effect on Years Ahead through Modules Mastered ($\beta = 0.052$, SE = 0.002, $p < .001$, 95 % CI [0.049, 0.056]).

When compared to Major Cities, students from Inner Regional schools showed a positive indirect effect on the Years Ahead variable through Modules Mastered ($\beta = 0.018$, SE = 0.001, $p < .001$, 95 % CI [0.016, 0.020]). Similarly, students from Outer Regional schools exhibited a positive indirect effect on Years Ahead through Modules Mastered ($\beta = 0.022$, SE = 0.001, $p < .001$, 95 % CI [0.020, 0.025]). Conversely, students from Remote and Very Remote schools demonstrate a negative indirect effect on Years Ahead through MM ($\beta = -0.011$, SE = 0.002, $p < .001$, 95 % CI [−0.015, −0.006]).

The results of the mediation analysis are summarised in Table 7, indicating ITS usage amplified the positive effects of socio-educational advantage, and the negative effects of rurality, upon student learning outcomes. Specifically, for students from Inner Regional areas, 66.7 % of the total effect on Years Ahead was mediated by Modules Mastered. For students from schools located in Remote and Very Remote areas, 52.4 % of the total effect on Years Ahead was mediated by Modules Mastered. With respect to socioeducational advantage, 54.7 % of the total effect on Years Ahead was mediated by Modules Mastered. These results indicate that ITS usage has an amplification effect on mathematics learning outcomes, where ITS usage amplifies the existing effects of socio-educational advantage and rurality upon Years Ahead.

4. Discussion

This study examined how ITS usage impacted the effect of socioeducational advantage and rurality upon mathematics learning outcomes in Australian high schools. Moreover, it examined whether ITS usage mediated the relationship between school socio-educational advantage and rurality, and student learning outcomes. This study used Structural Equation Modelling of secondary data from two datasets; the MySchool dataset of school sociodemographic characteristics, and the AdaptiveMath dataset containing student activity log metrics within the AdaptiveMath ITS platform. Given the cross-sectional nature of the data, this study cannot establish causal relationships, only associations.

4.1. Socioeducational advantage and Rurality's impact on ITS usage

Research question 1 considered the impact a school's socioeducational advantage had upon the ITS platform AdaptiveMath's usage within Australian high schools. The model found statistically significant, positive associations between a school's socioeducational advantage percentile, and the number of modules that their student's both completed and mastered. With regards to school rurality, statistically significant effects on both AdaptiveMath modules completed and mastered were also found across each of the school location categories, however a clear relationship correlating a school's rurality with ITS usage was not found.

Specifically, in relation to socioeducational advantage, an increase of 4.12 percentiles in a school's socioeducational advantage was associated with one additional Module Completed, and an increase of 8.77 percentiles in a school's socioeducational advantage was associated with one additional Module Mastered. However, the model only explained 69.4 % of the variance in modules mastered, and 3.5 % of the variance in modules completed, implying that while these relationships are statistically significant, there are other factors not featured in the model that may explain more nuance in ITS usage.

With regards to school rurality, although statistically significant, the degree of remoteness of schools and the number of Modules Completed and Modules Mastered by students was not clearly related. For example, while classified as being more rural than students from Major Cities, students attending schools located in Inner Regional areas completed fewer modules, but mastered more modules than their Major Cities counterparts. Moreover, students from schools in Outer Regional areas, who were even more rural, both completed and mastered more modules than students from schools located in Major Cities. It was only in the highest tier of rurality, which consisted of students attending schools located in Remote and Very Remote areas, were fewer modules both completed and mastered on the AdaptiveMath ITS platform than students from Major Cities. Despite not showing a linear relationship between rurality and its effect on ITS usage, the results indicate the importance of rurality in more remote settings relative to those in more urban contexts.

4.2. Socioeducational advantage and Rurality's impact on ITS outcomes

Research question 2 considered the impact a school's socioeducational advantage and rurality had upon student mathematics learning outcomes. The model found statistically significant, marginal effects of both socioeducational advantage and rurality upon the number of years ahead in terms of students' mathematics achievement level in AdaptiveMath, in comparison to their school year level. While there was a statistically significant positive relationship between a school's socioeducational advantage and how many Years Ahead a student was in the AdaptiveMath platform, the number of Years Ahead was marginal. For example, a comparison of schools of

Table 7
Standardised direct and indirect effects of socioeducational advantage and rurality on years ahead, mediated by modules mastered for the model.

Independent Variable (X)	Direct Effect on Modules Mastered (Path a)	Indirect Effect on Years Ahead (a × b)	Direct Effect on Years Ahead (Path c')	Total Effect on Years Ahead (c' + a x b)	Proportion of Total Effect Mediated by Modules Mastered (%)
Inner Regional	0.034	0.018	0.009	0.027	0.667 (66.7 %)
Outer Regional	0.041	0.022	−0.024	−0.002	0.478 (47.8 %)
Remote and Very Remote	−0.02	−0.011	−0.01	−0.021	0.524 (52.4 %)
Socioeducational Advantage	0.099	0.052	0.043	0.095	0.547 (54.7 %)

Note. Direct effect of Modules Mastered to Years Ahead (Path b) is $\beta = 0.529$.

Table 8
Standardised indirect effects of observed variables through modules mastered to years ahead in the AdaptiveMath platform for the model.

Path	β	SE	p	BC bootstrapped 95 % CI
Inner Regional → MM → YA	0.018	0.001	<0.001	[0.016, 0.020]
Outer Regional → MM → YA	0.022	0.001	<0.001	[0.020, 0.025]
Remote & Very Remote → MM → YA	−0.011	0.002	<0.001	[-0.015, −0.006]
SEA Percentile → MM → YA	0.052	0.002	<0.001	[0.049, 0.056]
Students to Teacher → MM → YA	0.001	0.001	0.627	[-0.002, 0.004]
Returned User → MM → YA	−0.022	0.001	<0.001	[-0.025, −0.019]
Starting Ach Lvl → MM → YA	0.058	0.001	<0.001	[0.055, 0.062]

Note. BC = bias corrected. CI = confidence interval. MM = modules mastered. YA = years ahead. SEA = socioeducational advantage. Ach. Lvl = Achievement Level.

the lowest percentile of socioeducational advantage with schools of the highest percentile, found the Years Ahead variable to differ only by 0.3. This finding aligns with the literature indicating that while ITS platforms can lead to improvements in learning outcomes, these gains are often modest and context-specific (Kulik & Fletcher, 2016; Muralidharan et al., 2019).

4.3. Relationship between ITS usage and ITS learning outcomes

Research question 3 considered whether usage of the AdaptiveMath ITS platform mediate mathematics learning outcomes. The following findings are based on several different measurements. Firstly, by considering the goodness of fit indices between each iterative model, the inclusion of ITS usage in the SEM was found to improve explained variance in learning outcomes by an additional 24.9 %, compared to when school and individual characteristics were included alone, suggesting that ITS usage plays a role in how socioeducational advantage and rurality impact learning outcomes.

Secondly, a mediation analysis indicated ITS usage mediated the effects of school socioeducational advantage and rurality on mathematics learning outcomes within the AdaptiveMath platform. Specifically, ITS usage amplified the effects of socioeducational advantage and rurality upon learning outcomes. The exception to this was schools located in Outer Regional areas, where ITS usage had a suppression effect on the negative effects impacting learning outcomes. These findings indicate a Matthew Effect (Mingo & Bracciale, 2018), where students who are already advantaged continue to benefit more from educational interventions than those who are less privileged (Lutz, 2019). This observed Matthew Effect is underscored by the broader literature on digital education, which suggests that technology can perpetuate and even exacerbate existing inequalities. For instance, Selwyn, Hillman, Bergviken Rensfeldt, and Perrotta (2023) and Rafalow (2020) noted that digital technologies often benefit those who are already advantaged, as these students typically have better support systems and more conducive learning environments than those who are less privileged.

Meanwhile, the suppression effect observed in Outer Regional areas suggests that while ITS platforms can mitigate some negative effects of rurality in some contexts, these benefits are limited and do not entirely remove the gap caused by broader structural inequalities (Van Dijk, 2020). The overall results support the existing view that while ITS platforms have potential, their effectiveness is heavily impacted by pre-existing disparities, thus calling into question the notion that technology alone can solve inequities in educational outcomes (Selwyn & Facer, 2021).

4.4. Contributions of this study

The current study contributes to the existing literature in several ways. First, it provides evidence supporting the Digital Divide, particularly in terms of the second and third levels of the Digital Divide. The results suggest that school socioeducational advantage and rurality affect student usage of ITS platforms. While these findings support the existence of the second level of the Digital Divide, the current results suggest more complexity in digital usage differences than previously asserted by Scheerder et al. (2017) and Van Dijk (2020).

Specifically, while statistically significant differences in learning outcomes were found between students from schools in Major Cities and those in rural areas, students in Inner Regional and Outer Regional schools mastered more modules than those from Major Cities, contrary to the initial hypothesis. These results indicate that rurality may not follow a linear relationship with ITS usage. Instead, the second level of the Digital Divide might only apply to schools that are significantly remote, with minimal or even positive effects in regional areas.

Regarding socioeducational advantage, a simpler, expected relationship between ITS usage and affluence was found, aligning with existing Digital Divide literature. Specifically, a statistically significant, positive relationship between socioeducational advantage and Modules Mastered and Completed was identified, supporting the findings of Scheerder et al. (2017) and Ma (2021).

However, it is important to acknowledge the limitations of this study. The cross-sectional nature of the data restricts the ability to make causal inferences and may fail to capture the dynamics of how ITS usage evolves over time. Longitudinal data would provide a more comprehensive understanding of the long-term effects of socioeducational advantage and rurality on ITS usage and learning outcomes, allowing for the establishment of causal relationships and a deeper exploration of how these factors interact over time. Further, diverse measures of ITS use including time spent on the platform or other engagement patterns could be used to capture a more nuanced understanding of student usage of ITS platforms.

4.5. Implications

Beyond its research contributions, the findings of this study have several implications for practice and policy. In summary, these findings are that socioeducational advantage and rurality have a statistically significant effect on ITS usage. Secondly, while socioeducational advantage and rurality have a statistically significant effect upon mathematics learning outcomes in the platform, they were marginal. Thirdly, a mediation effect was observed between use of the AdaptiveMath platform and mathematics learning outcomes, such that use of the AdaptiveMath platform amplified the positive effects of socioeducational advantage, and the negative effects of attending a remote and very remote school.

Firstly, the findings of this study offer several practical implications, specifically for ITS platform vendors, such as AdaptiveMath. Descriptive statistics of the analytic sample indicate the AdaptiveMath platform is used by a large number of students who are significantly behind academically or are those enrolled in regional or remote schools, as well as schools of low socioeducational advantage. Further, many of the students in the analytic sample used the AdaptiveMath platform for multiple years. This is particularly pertinent when descriptive statistics of this study also found students from affluent and urban schools to use the AdaptiveMath platform earlier in their schooling career, for more years, to have completed more modules on the platform, and be fewer years behind than their rural and less affluent peers. These findings should shape the outreach and engagement strategies of AdaptiveMath, who should bare a moral responsibility for student learning outcomes, especially when used in vulnerable communities for large portions of students' mathematics schooling (Selwyn, 2016). Policy makers and school leaders, too, should develop metrics for keeping ITS platforms accountable to improving student learning outcomes, and not reproducing further disparities.

Secondly, the findings of this study challenge the findings of Chevalère et al. (2022), whose own SEM analysis found both disadvantaged and highly privileged students taught using ITS platforms to experience similar improvement in academic achievement from using the platform, thus keeping "the socioeconomic achievement gap constant" (Chevalère et al., 2022, p. 368). Rather, with the inclusion of a mediation analysis, this study found that while the differences in learning outcomes in the platform across socioeducational advantage and rurality were marginal, these disparities were amplified by the use of the ITS platform. Specifically, ITS usage amplified the positive effects of socioeducational advantage, and the negative effects of attending a remote and very remote school, upon student learning outcomes. These findings should prompt both school leaders and ITS vendors such as AdaptiveMath to consider whether an ITS platform is really needed in remote schools or those of low socioeducational advantage. Where such an ITS platform is implemented, additional support should be provided to these schools to ensure use of the ITS platform doesn't exacerbate further education inequalities. Such support measures could include professional development for teachers, as well as targeted interventions for students enrolled in these schools so as to help them effectively engage with the technology. These practical recommendations can help schools tailor their use of ITS to better serve their students' unique needs, or even determine the appropriateness of using the platform at all, thereby potentially reducing educational disparities.

This study also has several policy implications, particularly with regard to promoting equitable access to quality education through technology. Although there is more work to do in connecting these findings to data from standardised tests, this study suggests that using ITS platforms may not narrow disparities in mathematics learning outcomes in rural or schools of low socioeducational advantage. Instead, a Matthew Effect (Mingo & Bracciale, 2018) could occur, where more advantaged students gain greater benefits from ITS platforms than their disadvantaged counterparts, potentially widening learning disparities.

Future policy must therefore focus on mitigating these disparities by developing tailored strategies that address the specific needs of disadvantaged students, and encourage the adoption of ITS platform in ways that are more equitable. By addressing these factors, educational policies can help create a more equitable environment that leverages technology to enhance learning outcomes for all students.

Taken together, these findings suggest a need for a more nuanced understanding of the second and third levels of the Digital Divide; namely, it may not be appropriate to consider rurality as having a comparable effect on digital use as socioeducational advantage or affluence, as has been the case in previous studies such as Park (2022), seeking to quantify the Digital Divide in rural Australia. Further, considering rurality a dichotomous variable purely determined by population size, such as in Kormos and Wisdom (2021)'s work on rural schools and the Digital Divide, may also be unhelpful, as the findings of this study indicate that regional schools have a substantially different experience of using ITS platforms than remote schools. Rather, there may be other factors within rural schools that allow their students to have higher rates of ITS usage. Examples of such factors could include differences in classroom routine, teacher training, or cultures of technology use in a student's school or family, such as those identified in Rafalow (2020)'s ethnography, which result in students from these schools being more effective in their use of ITS platforms.

5. Conclusion

This study set out to explore how ITS usage impacts the effect of socioeducational advantage and rurality upon mathematics learning outcomes in Australian high schools. Research question 1 considered the relationship between school socioeducational advantage and rurality, and students' usage of the ITS platform AdaptiveMath. Research question 2 considered how school socioeducational advantage and rurality related to learning outcomes within the AdaptiveMath platform. Finally, research question 3 considered the mediating relationship between usage of AdaptiveMath and learning outcomes within the platform.

The findings reveal marginal, but statistically significant relationships between the socioeducational advantage and rurality of a student's school, and the ITS usage metrics and learning outcomes of their students. Specifically, students from more affluent and urban schools used the ITS platform earlier in their schooling career, for more years, completed more modules, and achieved higher learning outcomes, compared to their rural, less affluent peers. Additionally, ITS usage was found to mediate the effects of socioeducational advantage and rurality, amplifying their impact on learning outcomes.

These results suggest that introducing technology alone in rural, less affluent schools will not reduce achievement gaps in student mathematics performance. Rather, trying to reduce educational disparities simply by providing ITS platforms, without considering the specific context of the schools in which they are implemented, may instead benefit students attending privileged schools more greatly, reflecting a Matthew Effect (Mingo & Bracciale, 2018) of even greater learning disparities.

In conclusion, while ITS platforms show potential for improving mathematics learning outcomes, their effectiveness is heavily influenced by the socioeducational and geographical context of their implementation. This study contributes to the understanding of the Digital Divide within the school context, and offers insights into ITS effectiveness for researchers, educators, and policymakers. Future research should continue to explore these relationships through longitudinal and qualitative studies and incorporate standardised assessment measures to provide a more comprehensive evaluation of ITS effectiveness.

CRediT authorship contribution statement

Brody Hannan: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Rebecca Eynon:** Writing – review & editing, Supervision, Conceptualization.

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Data availability

The authors do not have permission to share data.

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