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Exploring growth mindset and mathematics achievement using quantile regression: A study in Malaysia

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ABSTRACT

In the most recent PISA assessment, Malaysia faced the steepest drop in mathematics achievement that had ever been recorded in the previous PISA cycle. Many factors may contribute to this decline. One factor that has gained significant attention in recent years is the growth mindset. However, limited research has focused on its impact in Malaysia. This study explored the relationship between growth mindset and mathematics achievement, focusing on low-performing and high-performing Grade 7 students in Kota Kinabalu, Malaysia. A total of 686 Grade 7 students from secondary schools in Kota Kinabalu were selected to participate in this study. The instrument used in this study was a validated self-report Growth Mindset scale, and an end of the academic session examination (UASA) paper prepared by the Malaysian Examination Board. Ordinary least squares (OLS) regression and quantile regression analysis were employed to explore whether growth mindset varied across mathematics achievement levels among students. The results revealed that the positive effect of growth mindset was greater for high-performing students than for low-performing students. These findings indicate that while growth mindset interventions benefit all students, low-performing students require integrated support addressing both mindset and foundational mathematical competencies. Implications for differentiated intervention design are discussed.

Keywords: quantile regression, linear regression, growth mindset, mathematics achievement, low-performing students, high-performing students

INTRODUCTION

In the most recent PISA 2022 assessment, Malaysia encountered the steepest decline in mathematics achievement ever recorded in the previous PISA cycle. Similarly, a decreasing trend is also evident in another large-scale international assessment, the Trends in Mathematics and Science Study (TIMSS). Upon further research into the recent PISA mathematics results, we found that nearly 60% of Malaysian students scored below the baseline level of mathematics proficiency. The large number of students below the mathematics proficiency baseline level is alarming. This decreasing trend raises concerns among Malaysian policymakers and educators, as it can affect long-term economic growth and the preparedness of future Malaysian generations to compete in the global labour market.

These concerns reveal that mathematics achievement is a critical issue that requires immediate attention. While many factors are linked with poor performance in mathematics, one of the psychological factors that has gained significant attention in recent years is the growth mindset. Previous studies have shown that including growth mindset intervention in mathematics subject can significantly reduce mathematics anxiety (Samuel et al., 2023). A growing number of previous studies have started to explore growth mindset on mathematics achievement. It can also be observed in PISA questionnaires, which have started to include growth mindset items since 2018. This inclusion highlights the importance of the growth mindset in influencing students' academic outcomes globally.

With this concern in mind, this study aims to understand whether a growth mindset has different effects on students with different mathematics performance levels. Thus, the research question is as follows:

RQ1 Does a growth mindset relate to mathematics achievement for Grade 7 students?

RQ2 Does the growth mindsetdiffer significantly among low, medium, and high-achieving students in mathematics?

LITERATURE REVIEW

Theoretical Foundations of Growth Mindset

Mindset is defined as the mental frame or lens that selectively organizes and encodes information (Crum et al., 2013). It is a psychological construct that refers to a person's belief about their abilities and intelligence (Dweck, 2006). Growth mindset construct develops from the implicit theories of intelligence (Dweck, 2006). According to the implicit theories of intelligence, there are two distinct concepts of intelligence: Entity theory and incremental theory (Dweck & Leggett, 1988). Today, the entity theory is described as a fixed mindset and the incremental theory as growth mindset. A person with a fixed mindset believes that intelligence and ability are fixed and cannot be changed (Dweck, 2006; Yeager & Dweck, 2020). Fixed mindset students tend to set performance goals that lead to maladaptive behaviours (Dweck & Leggett, 1988). They focus on proving their ability and prioritising looking smart in front of people. They also do not like negative judgements or challenging tasks. A person with a growth mindset views abilities as something that can be developed through effort, learning, and perseverance (Yeager & Dweck, 2020). They tend to adopt learning goals and focus on developing their abilities rather than proving them. This focus leads to adaptive behaviours such as persist when faced with failure, optimism with negative judgement, seeking challenges as opportunities to grow (Dweck & Leggett, 1988). According to Dweck (2006), growth mindset applies to all aspects of life and is not limited to education alone. However, the growth mindset and fixed mindset in this study focused on mathematics education.

Growth Mindset and Mathematics Achievement

Mathematics is a subject with many abstract concepts. It develops over time from prior knowledge. Students must learn basic concepts before they can proceed to a more advanced concept. To succeed in mathematics, students also need to invest more time, practice, and patience. However, students with low mathematics self-efficacy may develop negative perception of mathematics when they repeatedly fail to master prior mathematics concepts. Over time, they may start to dislike mathematics and avoid mathematics tasks (Aguilar, 2021). It is no surprise that many students develop low self-perception of their ability in mathematics (Appiah et al., 2022; Mitchell & George, 2022). They often show a tendency to believe that they cannot do well in mathematics no matter how hard they try (Schnitzler et al., 2021).

One of the psychological factors that has gained significant attention in recent years is growth mindset. Previous research has found that growth mindset interventions have been reported to help students overcome their mathematics anxiety and be more motivated to do mathematics tasks. For instance, Samuel et al. (2023) have found that students tend to be more motivated to perform mathematics tasks and have less anxiety in mathematics tasks after being introduced to growth mindset interventions. Although both the experiment group and the control group also shown improvement in mathematics self-efficacy, but the qualitative data showed that students believe that the growth mindset intervention motivated them to persist when faced with difficult mathematics questions. Additionally, another large-scale research study conducted with over 12,000 ninth-grade students in the United States shows that two 25-minute online mindset sessions significantly improved the mathematics performance of low-achieving students. Students in the study also showed greater interest in enrolling in advanced mathematics courses in the 10th grade.

Similarly, previous researchers such as Lee et al. (2021) and Outes-Leon et al. (2020) have demonstrated the same positive outcomes, supporting the idea that introducing a growth mindset into curricula or pedagogy can improve student academic performance.

Although most studies have shown a positive relationship between growth mindset and mathematics performance, some studies have shown different results. For instance, Huillery et al. (2021) revealed that low-achieving students did not benefit from growth mindset strategies as fast as other high-achieving students with better behaviour and stronger motivation (Huillery et al., 2021). Results from the study show that longer and more consistent growth mindset interventions are needed to improve academic outcomes for students from disadvantaged backgrounds. This study is aligned with the meta-analysis conducted by Macnamara and Burgoyne (2023). They stated that the effects of growth mindset interventions on academic achievement were minimal and often not significant at all.

However, Tipton et al. (2023) compared both Macnamara and Burgoyne (2023) and Burnette et al. (2023) meta-analysis results. They found that Macnamara and Burgoyne's study was not reliable because they used a traditional meta-analysis, "Aggregated effect size," which is less effective in understanding heterogeneous studies. In contrast, the modern multi-level meta-regression method used by Burnette et al. (2023) with the R package software is more reliable for heterogeneity analysis. In other words, Tipton et al. (2023) supported Burnette et al. (2023) outcomes where the growth mindset intervention works better for students who struggle in academics compared to those who are high performers.

Quantile Regression in Educational Research

Quantile regression is a statistical approach used to estimate the conditional quantiles of a dependent variable, given a set of predictors (Koenker, 2005). It was introduced by Roger Koenker in 1978. Quantile regression is an extension of OLS regression, but it has several advantages over OLS regression. Quantile regression gives a more complete view of the relationship between variables by estimating different quantiles (Koenker, 2005). It can handle skewed and non-normal data more effectively because it is more tolerant of outliers (Xu, 2023), unlike OLS regression, which focuses solely on estimating the mean of the dependent variable. The ability to model different parts of quantile regression makes it a better option for heteroscedastic data (Jung et al., 2015).

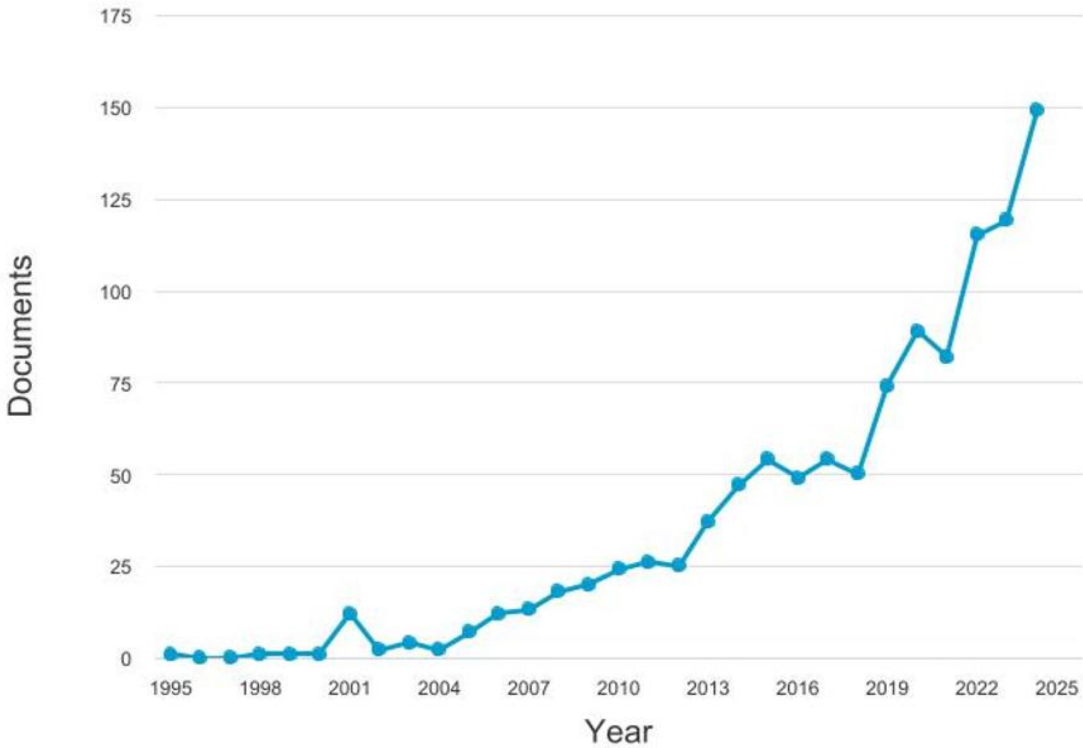

Figure 1. Growth in publications applying quantile regression to educational research from 1995 to 2024 (Source: Authors' own elaboration, based on data from Scopus)

Over the past two decades, the number of publications on quantile regression in the education field has been rising. As shown in **Figure 1**, the rising trend since 2010 indicates that more researchers are beginning to recognize its benefits in the educational field, even though it is less common compared to a more robust statistical method, such as structural equation modelling (SEM). Most educational research employs quantile regression to investigate the impacts of various factors on student performance at different levels. For instance, Dong et al. (2022) used quantile regression to understand the relationship between executive function (EF) and mathematics competencies in children. Results revealed that the predictors had a strong positive relationship with mathematics performance for children with lower mathematics competency compared to children with medium or higher competency. Similarly, previous studies such as Barnes et al. (2024) and Volodina et al. (2021) used quantile regression to analyse how students vary at different achievement levels. In addition, some researchers used quantile regression to analyse international large-scale assessments. For example, Perry et al. (2022) and Flannery et al. (2023) examined the effect of school socioeconomic status (SES) on academic achievement using the PISA database.

Other than academic performance, quantile regression is also used in other educational fields, such as examining how students or teachers vary across different quantiles of factors like stress levels, well-being, social-emotional skills, overall student well-being, and more (e.g., Da Silva et al., 2024; Wang et al., 2022). For instance, Wang et al. (2022) used quantile regression to examine how cooperative and competitive school climates affect students' social and emotional skills at various levels. In this study, secondary school students are divided into five quantiles: 10%, 25%, 50%, 75%, and 90%. The results showed that students with higher skill levels had a more positive impact from a cooperative school climate. These findings highlight the advantages of quantile regression over the OLS regression method as it offers a richer understanding of the heterogeneous nature of educational data.

METHODOLOGY

Participants

This was a cross-sectional correlational design study. This study was conducted at a single time point to explore the relationship between mathematics achievement and growth mindset. The participants of this study comprised 686 Grade 7 students, and they were selected randomly from the public secondary schools in Kota Kinabalu, Sabah. The rationale for selecting this group of students was that they had recently transitioned from primary school to secondary school, entering a new environment and curriculum. It is worth understanding how their mindset influenced their academic performance during this transition period.

Instruments

Mindset measures

This study adapted four items from the Implicit Theories Scale to measure the growth mindset of participants. In this study, the participants responded to the items using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Total scores ranged from 4 to 20, with higher scores indicating a stronger fixed mindset. Originally, there were four entity theory (fixed mindset) items and four incremental theory (growth mindset) items. Altogether there were eight items from the Implicit Theories Scale (Dweck, 1999). Measurement items are presented in the **Appendix**. This decision is because there was concern that respondents might respond to the incremental theory items in a socially acceptable manner rather than genuinely (Claro et al., 2016; Puusepp et al., 2021). According to Stocke (2001), respondents tend to answer positive questions in a way that they think is acceptable to society. This leads to biased responses and reduces the accuracy and reliability of the measures. It is acknowledged that using only fixed mindset items may increase the possibility of acquiescence bias. At the same time, although using only fixed mindset items may reduce the social desirability bias, it may reduce the construct coverage. Thus, growth mindset in this study was measured indirectly through students' level of agreement with fixed mindset beliefs. Lower level of agreement with fixed mindset beliefs indicates higher growth mindset tendencies.

The construct in the pilot test had a Cronbach's alpha of 0.76, which was above the acceptable threshold of 0.70. Additionally, we have reworded the items after two rounds of pilot testing. The rewording was done to help the 13-year-old participants easily grasp the meaning of the items. After rewording, Cronbach's alpha for the measure was 0.8108. All items had item-total correlations ranging from 0.429 to 0.609. This result indicates that the items have relatively high internal consistency, making the measure reliable for the study (Hajjar, 2018). In addition, factor analysis confirmed the construct validity of this measure, with all factor loadings in the acceptable range (0.712 - 0.838).

Mathematics achievement

This study adopted the final academic session test (UASA) to assess the mathematics proficiency of Grade 7 students. The total score ranged from 0 to 100, with higher score indicating higher mathematics achievement. UASA is a national-level test conducted once per academic year within a timeframe set by the Malaysia Ministry of Education (MOE). Since this study was intended to be carried out in July, when most of the schools had only covered seven out of the 13 Grade 7 mathematics syllabus, the mathematics test only included seven Grade 7 mathematics topics. The testing time, which was initially 2 hours, was reduced to 1 hour to minimise the student learning time lost. Since each school generates its exam paper by selecting questions from the question bank provided by the MOE, this study randomly chose four UASA mathematics papers. Then, the items from these four papers were selected following the outline of the Test Specification Table (JSU) and Item Specification Table (JSI).

The JSU is based on the Standard Curriculum and Assessment Document (DSKP), which outlines the topics and subtopics that students should learn each year for a specific subject. It also classifies the UASA items based on the six levels of Bloom's Taxonomy cognitive skills. In each cognitive skill level, the items are further organised into three different difficulty levels: Easy, moderate, and hard. These steps ensure that UASA items are covered equally by all expected learn topics with balanced difficulty levels. It also ensures that the distribution of items in the six levels of cognitive skills is balanced. Overall, the JSU provides a framework for the entire UASA test.

On the other hand, the JSI is an extension of JSU, focusing on the micro details of each item. Similar to JSU, the JSI also consists of cognitive levels, difficulty levels and subtopics, but these are specific to each item. Additionally, it indicates whether the item is an objective or subjective question. Each item is further analysed to determine the type of thinking skills being assessed, whether it is knowledge application, problem-solving, or critical thinking. These steps are crucial to ensure the items are valid and reliable for assessing students' abilities.

Data Collection

Before starting the data collection process, permission was obtained from the Ministry of Education (MOE) via the Educational Research Application System (ERAS). After confirmation from MOE, another layer of permission was obtained from the Sabah State Educational Department (JPN) and the Kota Kinabalu district educational department (PPDKK). After that, we bought these permission letters to meet the school's principal or administrator. After receiving the green light and class arrangement from the administrator, we met the students who participated in the study and distributed the parental consent letter to them.

The data from the pilot test and actual test were collected using paper-based questionnaires and mathematics tests. These instruments served different measurement purposes. Questionnaire was used to measure students' growth mindset, while mathematics test was used to assess students' mathematics achievement. The rationale for using paper-based instruments instead of online instruments was that the number of computers in some schools was very limited. Furthermore, the school's computer laboratory was usually occupied by classroom sessions and other routine school events.

After collecting and marking the mathematics test papers based on the answer scheme, we inserted the data into an Excel file. We coded each participant to make the key-in process more organized. We then performed data cleaning and treated the missing values. Prior to the actual data analysis, responses from participants who left the class for unexpected ad hoc activities were excluded.

Data Analysis

In this study, both ordinary least squares (OLS) regression and quantile regression were conducted for comparison. OLS regression helped to provide the average effect of mindset on mathematics achievement. In contrast, quantile regression helped to identify whether growth mindset has a varying effect on student's mathematics achievement across the distribution. These two approaches ensure a more comprehensive analysis by offering a comparison of results. From the comparison, we can see whether the mindset influences students differently at different levels of mathematics achievement. This study used the R package to run both the OLS regression and quantile regression analyses. Quantile regression is an extension of the traditional ordinary least squares regression. The equation for the OLS estimated regression coefficients $\hat{\beta}$ is obtained by minimising the residual sum of squares, given as follows (Hastie et al., 2009):

$$\hat{\beta} = \underset{\beta}{argmin} \sum_{i=1}^{n} \left(MATH_i - X_i^{\top} \beta\right)^2 \tag{1}$$

where $MATH_i$ is the ith observed mathematics achievement score, $X_i^{\top}$ is the ith observed row of the design matrix X, and β is the regression coefficient vector. For quantile regression coefficient estimates ($\hat{\beta}_\tau$), there is no closed-form solution. It provides a more detailed picture than OLS because it allows quantile prediction rather than mean prediction. $\hat{\beta}_\tau$ can be found by solving the following optimization problem using the check function $p_\tau(u)$ (Hastie et al., 2009; Koenker & Bassett, 1978):

$$\hat{\beta}(\tau) = \underset{\beta}{argmin} \sum_{i=1}^{n} \rho_\tau\left(MATH_i - X_i^{\top} \beta\right) \tag{2}$$

$$p_\tau(u) = \begin{cases} \tau u, u \geq 0 \\ (\tau - 1)u, u < 0 \end{cases} \tag{3}$$

Check function $p_\tau(u)$ treats positive and negative residual (u) differently. A residual is considered positive if the actual value is higher than the predicted value. If the actual value is lower than the predicted value, then the residual is negative. Different weights are assigned to positive and negative residuals depending on the quantile. Positive residuals are multiplied by τ while negative residuals are multiplied by $(\tau - 1)$. After estimating the coefficients, the Goodness-of-fit is then assessed to evaluate how well the model explains the variation in the data. For OLS regression, goodness-of-fit is calculated as follows (McClave et al., 2008):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}\right)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{4}$$

where $\widehat{Y_\iota}$ is the predicted value of Y_i from quantile regression, $\overline{Y_\iota}$ is the mean of all observed values of Y_i. For quantile regression, pseudo-R² (${R_\tau}^2$), proposed by Koenker & Machado (1999), was used to measure the model goodness-of-fit:

$${R_\tau}^2 = 1 - \frac{\sum_{i=1}^{n} \rho_\tau\left(MATH_i - \hat{Y}_i(\tau)\right)}{\sum_{i=1}^{n} \rho_\tau(MATH_i - \hat{q}_\tau)} \tag{5}$$

The R-package generates all the coefficients and fit statistics, and manual calculation is not required. However, it is worth having a basic understanding of how these coefficients and fit statistics work and not relying on software mindlessly.

RESULTS

The demographic characteristics of the respondents are summarised in **Table 1**. The gender composition was relatively balanced, with a slightly higher percentage of female students (54.4%), while 45.6% were male students. In terms of ethnic group composition, Sabah natives form the largest group (73%), followed by Malays (11.7%), and Chinese (9.3%), who are the next two largest groups in this study. For household income, the most significant proportion of respondents fell in the lower-to-middle-income range, with 71% reporting a household income of less than RM5,249 per month. Only 9.9% of respondents reported that their household income exceeded RM11,820 per month.

Table 1. Descriptive analysis of the respondents

Variable	Categories	Frequency (n)	Percentage (%)
Gender	Male	313	45.6
	Female	373	54.4
Ethnic Group	Sabah native	501	73.0
	Chinese	64	9.3
	Malay	80	11.7
	Sarawak native	9	1.3
	India	2	0.3
	Others	30	4.4
Household Income	< RM2,560 per month	236	34.4
	RM2,560 – RM5,249 per month	251	36.6
	RM5,250 – RM11,819 per month	131	19.1
	RM11,820 – RM15,869 per month	47	6.9
	> RM15,869 per month	21	3.0

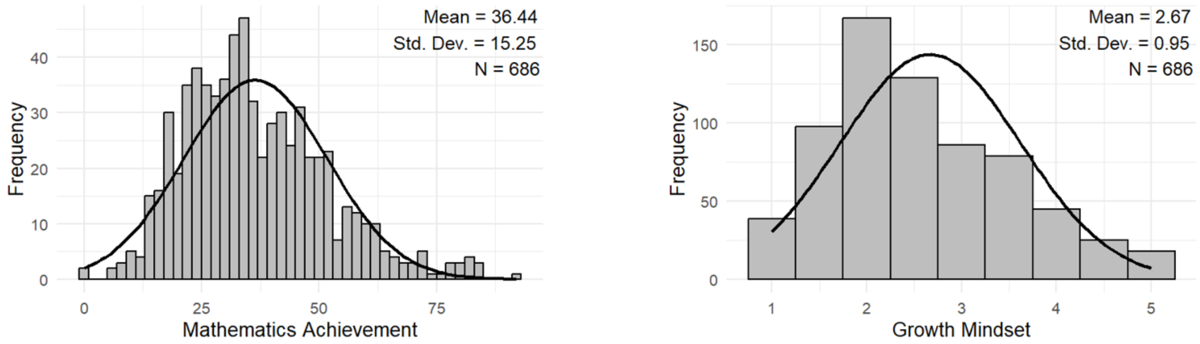

Figure 2. Histogram for all the continuous variables (Source: Author's own elaboration, using R statistical software)

Figure 3. Scatterplot for the effect of growth mindset on mathematical achievement (Source: Author's own elaboration, using R statistical software)

For the UASA scores, the mean was 36.44 and the standard deviation was 15.23. The histogram on the left side of **Figure 2** shows that the UASA score distribution is close to a bell-shaped curve, with a few students obtaining higher scores. However, the histogram of growth mindset shown on the right of **Figure 2** was slightly skewed towards the left with a mean of 2.67 and a standard deviation of 0.95, indicating that the overall tendency of students in this sample leans towards a fixed mindset rather than a growth mindset.

Then, a Pearson correlation analysis was conducted to examine the relationship between growth mindset and mathematics achievement. The results indicated a significant, moderate positive correlation between mathematics achievement and growth mindset, $r = 0.34$, $p < 0.01$, as shown in **Figure 3**.

A boxplot analysis (**Figure 4**) was conducted to explore the relationship between gender, ethnic groups, and household income levels and mathematics achievement. The findings suggest that these demographic factors exhibit varying associations with mathematics achievement. By including them as control variables, a better understanding of the relationship between growth mindset and mathematics achievement can be obtained.

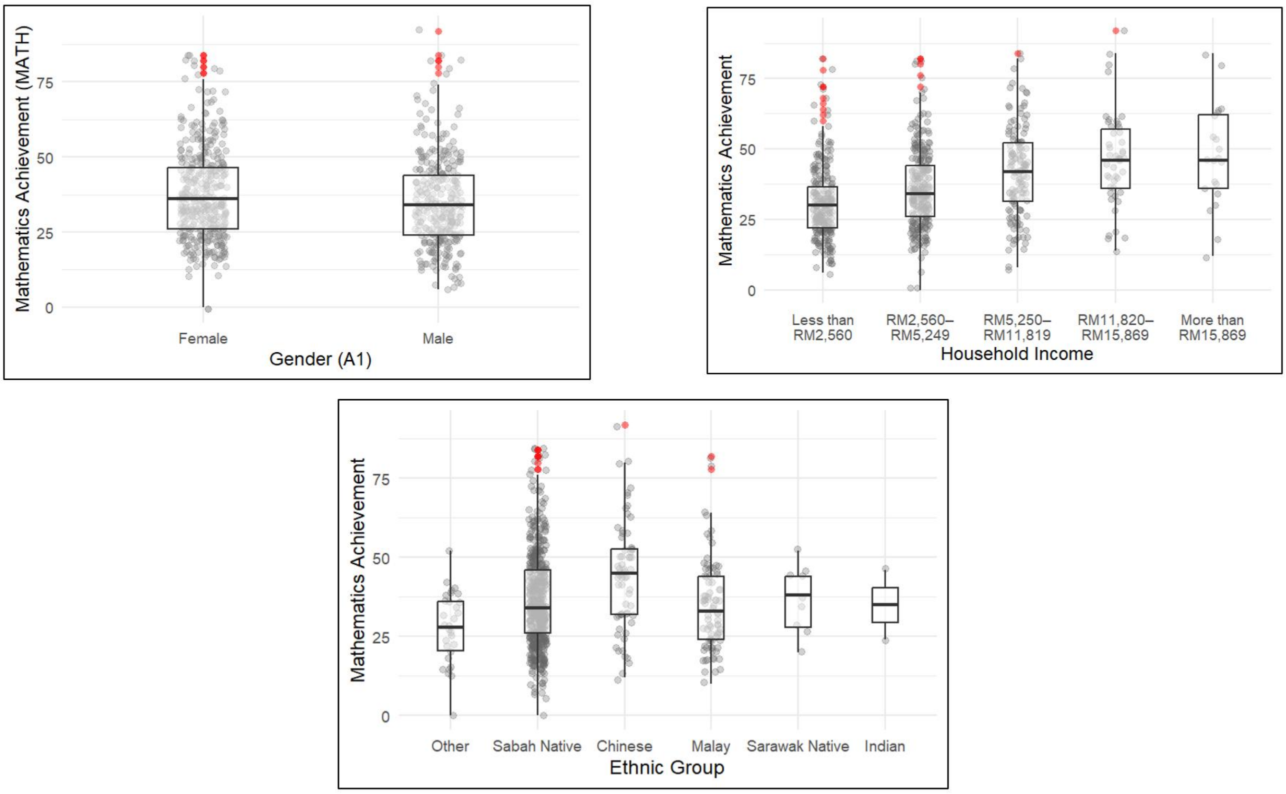

Figure 4. Boxplots of mathematics achievement across gender, household income levels and ethnic group (Source: Author's own elaboration, using R statistical software)

Table 2. Linear regression results

Predictor	**OLS (mean)**	
	Estimate	SE
Intercept	28.929**	4.178
Growth mindset	4.772**	0.562
Gender		
Male	-4.555**	1.050
Household income		
Less than RM2,560 per month	-13.512**	3.114
RM2,560 – RM5,249 per month	-9.542**	3.098
RM5,250 – RM11,819 per month	-4.255	3.185
RM11,820 – RM15,869 per month	-0.595	3.548
Ethnic group		
Sabah native	5.979*	2.531
Chinese	11.630**	2.990
Malay	2.221	2.888
Sarawak native	6.980	5.095
Indian	4.258	9.902
Model fit	R^2= 0.243 F(11,674) = 19.62**	

Reference category: Household income (> RM15,869 per month); Gender (female); Ethnic group = (others).
*p < 0.05; **p < 0.01

Subsequently, a multiple linear regression analysis was conducted to further explore the relationship between growth mindset and mathematics achievement by controlling for other variables, such as gender, ethnic group, and household income. As shown in **Table 2**, the regression model is statistically significant, F (11, 674) = 19.62, p < 0.001, explaining 24.3% of the variance in mathematics achievement. Growth mindset ($\hat{\beta} = 4.772, P < 0.001$) had a statistically significant positive effect on mathematics achievement after controlling for gender, household income, and ethnic group.

This study employed quantile regression at three different percentiles (25th percentile, 50th percentile, and 75th percentile) to investigate how the growth mindset affects mathematics achievement among low, average and high-achieving students. For the quantile regression model, standard errors and p-values were computed using the bootstrapping method, as they cannot be calculated using the standard least squares method. Additionally, some subcategories have a small sample size. Thus, bootstrapping provides more reliable estimates. The results revealed that a growth mindset was statistically significant in predicting mathematics achievement across all three quantile levels.

Table 3. Quantile regression results

Predictor	Quantile regresion					
	25th percentile		50th percentile		75th percentile	
	Estimate	***SE***	**Estimate**	***SE***	**Estimate**	***SE***
Intersept	23.111**	5.334	28.444**	5.916	37.600**	8.392
Growth mindset	3.556**	0.805	4.444**	0.807	4.800**	0.926
Gender						
Male	-3.111**	1.191	-4.889**	1.302	-4.000*	1.611
Household Income						
Less than RM2,560 per month	-13.778**	4.122	-12.667**	4.349	-14.400*	6.749
RM2,560 – RM5,249 per month	-10.889*	4.198	-8.222	4.253	-9.600	6.719
RM5,250 – RM11,819 per month	-6.000	4.352	-2.889	4.432	-2.000	6.609
RM11,820 – RM15,869 per month	-2.222	4.880	0	4.722	-2.000	6.960
Ethnic Group						
Sabah Native	5.778*	2.626	5.333	3.129	4.400	3.893
Chinese	12.222**	3.783	10.222*	4.020	11.200*	4.861
Malay	3.111	2.964	2.667	3.512	0.400	4.296
Sarawak Native	12.222**	4.524	5.333	4.452	-2.000	8.786
Indian	11.778*	5.102	4.667	4.616	-2.400	6.280
Model fit	Pseudo R^2 0.102		Pseudo R^2 0.144		Pseudo R^2 0.162	

Reference category: Household income (> RM15,869 per month); Gender (female); Ethnic group = (others). Bootstrapped standard errors with 200 replications. *p < 0.05; **p < 0.01

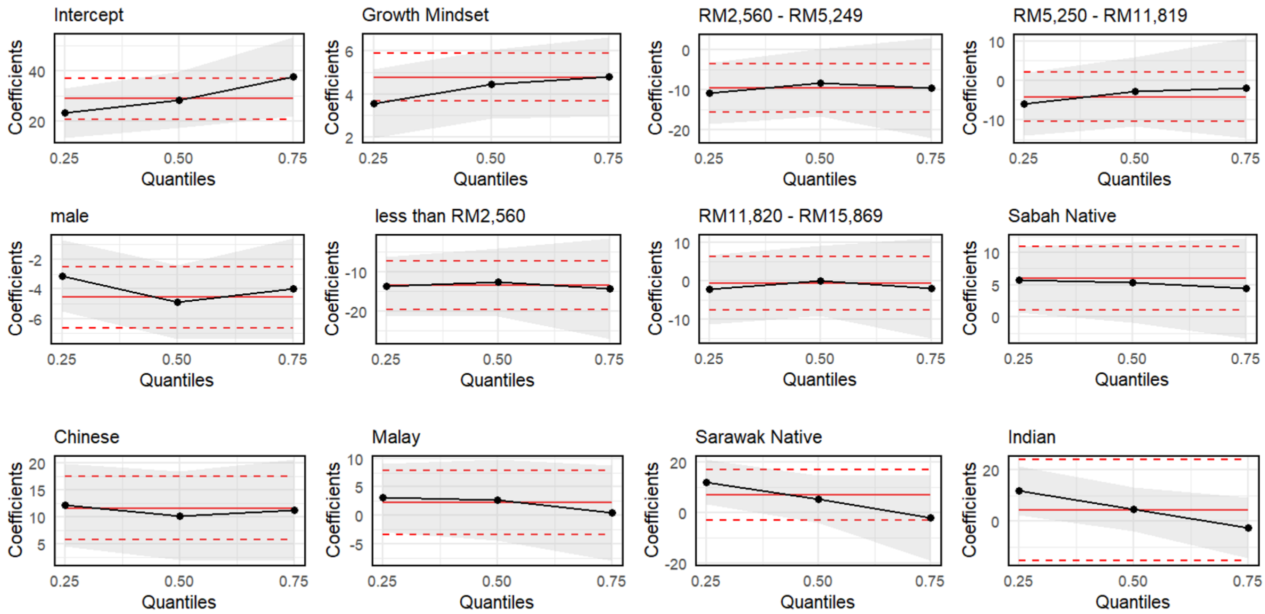

Figure 5. Quantile coefficients plot for growth mindset as predictor (Source: Author's own elaboration, using R statistical software)

However, the effect size differed across the three quantiles, as shown in **Table 3**. The effect size of growth mindset was smaller for low achievers at the 25th percentile ($\hat{\beta}_{0.25} = 3.556, p < 0.001$) compared to high achievers ($\hat{\beta}_{0.75} = 4.800, p < 0.001$) at 75th percentile. These findings suggest that the effect of growth mindset on mathematics achievement is more substantial among higher-achieving students. The results indicate that students who already perform well in mathematics tend to benefit more from growth mindset interventions than low-achieving students. Control variables, such as gender, household income, and ethnic group were included in the model as they have been shown to influence academic performance in previous research (e.g., Cooper & Stewart, 2021; Govindarajoo et al., 2022; Saadat & Sultana, 2024). While some of them were statistically significant in predicting mathematics achievement, they are not the primary focus of this study.

Figure 5 illustrates how growth mindset and other control variables affect mathematics achievement across different quantiles. The black line represents the estimated coefficients of quantile regression, and the grey shaded area represents the quantile regression confidence intervals. The solid red line represents the OLS coefficients, and the red dashed lines represent the confidence intervals of the OLS coefficients. These lines were compared, and we found that the effect of growth mindset is not uniform across different achievement levels, unlike the constant effect estimated by the OLS regression coefficients. In quantile regression, the estimated coefficient size was larger for high-performing students than for medium and low-performing categories.

Figure 6 presents the quantile regression analysis prediction lines. The blue line at the lower end represents the 25th percentile prediction line, the red line in the middle represents the 50th percentile prediction line, and the green line at the upper end represents the 75th percentile. All three lines exhibited a positive slope. However, the prediction line of the 75th percentile was steeper than the 25th percentile.

Figure 6. Quantile regression prediction lines (Source: Author's own elaboration, using R statistical software)

DISCUSSIONS AND RECOMMENDATIONS

The first objective of this study was to investigate whether growth mindset is related to mathematics achievement for Grade 7 students. According to the results of the Pearson correlation analysis, the growth mindset has a moderate positive ($r = 0.34$, $p < 0.01$) relationship with mathematics performance across all levels. The finding is consistent with the social-cognitive model of implicit theory introduced by Dweck (Dweck, 1986). According to Dweck's social-cognitive model, an individual who holds a belief in growth mindset tends to adopt mastery-oriented goals and adaptive responses during difficult tasks, while an individual who holds a fixed mindset tends to adopt performance goals and maladaptive responses (Lee et al., 2024). Students with a growth mindset believe that intelligence is malleable and can be grown and improved through practice. This perspective enables them to set mastery-oriented achievement goals and view failures as opportunities for learning rather than a negative judgement of their abilities (Lee et al., 2024). Hence, this group of students is more likely to respond adaptively and persist in deeper learning with challenging mathematical problems, leading to better mathematics achievement. In contrast, students with a fixed mindset often view intelligence as fixed and beyond their control. They usually set performance goals that focus on demonstrating rather than developing competence. This type of achievement goal can lead to maladaptive behaviours (Lee et al., 2024). They tend to avoid challenging tasks and protect themselves from negative judgments. Consequently, students with a fixed mindset are less engaged with challenging mathematical problems, leading to poorer mathematics achievement.

The significant positive association between a growth mindset and mathematics achievement observed in this study is aligned with many previous studies. In the context of correlational studies, growth mindset has been consistently linked with positive mathematics outcomes (e.g., Su et al., 2021). For instance, Su et al. (2021) reported a similar pattern in their cross-sectional study on 466 fifth grade student in China, where students with stronger growth mindset showed higher mathematics achievement not only directly but indirectly through mathematics self-efficacy and failure beliefs. This pattern has also been observed in other previous studies on secondary school students (e.g., Chen et al., 2024).

Not only cross-sectional research but also some experimental intervention studies have confirmed that students with growth mindset demonstrate higher academic resilience (e.g., Balan & Sjöwall, 2023). For instance, Huang et al. (2022) found that a 90-minutes growth mindset intervention benefits Chinese primary and secondary school students by increasing their intrinsic motivation, leading to greater mathematics achievement. At even broader levels, large-scale international studies have also reported that a growth mindset is associated with greater achievement (e.g., Kismiantini et al., 2021). For example, using the PISA 2018 database, Kismiantini et al. (2021) found that Indonesian students demonstrated higher mathematics scores when their growth mindset level is higher. Not only Indonesian students but also students from other countries demonstrated the same pattern in large-scale studies (e.g., Yeager et al., 2019). In summary, the number of studies demonstrating a positive correlation between growth mindset and mathematics achievement is expanding.

It is important to note that the average growth mindset score was 2.7 out of 5.0. The result indicated that respondents lean towards a fixed mindset rather than a growth mindset. From a mathematical education perspective, students with fixed-mindset tendencies are less motivated to engage with challenging mathematical tasks. They tend to be more pessimistic about negative judgm.0ent. The results highlight the need for educational policies to emphasise learning progress, effort, and the use of strategies rather than focusing on performance outcomes.

Another point is that prior research has reported mixed findings regarding the relationship between students' background characteristics and mathematics achievement. For instance, Krishnan et al. (2023) assessed the effect of socio-economic status (SES) on mathematics achievement and found statistically significant positive associations. To account for differences in students' background characteristics, such as ethnicity, household income, and gender, these variables were treated as control variables in this study. This step helps focus on assessing how a growth mindset affects mathematics achievement, without being influenced by students' characteristic backgrounds. In terms of policy implications, the results indicated a positive association between a growth mindset and mathematics achievement across diverse ethnic groups in Malaysia.

The second objective of the study was to examine whether growth mindset varies at different performing levels at the 25^{th}, 50^{th}, and 75^{th} percentiles. Based on the quantile regression results, the relationship varied across different quantiles of mathematics achievement. It was further confirmed with the Wald test (F(2,2065) = 4.82, $p = 0.008$). obtained from the R-package which showed that all three percentiles' slopes were significantly different, indicating there is a significant difference in effect size at different percentiles. Growth mindset has a stronger impact on mathematics achievement among higher-performing students. This finding suggests that although growth mindset benefits all students, it is more pronounced among students who are already good at mathematics.

One possible factor that makes high-performing students have higher mathematics confidence is that they already have a solid foundation in mathematics. In other words, when they have mastered the mathematics foundation, they are more confident and resilient to failure compared to low-performing students. This result is consistent with Dweck and Yeager (2019), who stated that students with growth mindset are more perseverant when faced with challenging work. People with a growth mindset tend to view the brain as a malleable muscle that can form stronger connections with plenty of learning (Dweck & Yeager, 2019). They believe their abilities can be enhanced through effort and practice. This is supported by neuroscience research, which found a larger error positivity (Pe) signal in the brain when individuals with a growth mindset spend more attention to their mistakes (Schroder et al., 2017). This heightened neural response to errors indicated the brain's ability to use mistakes as learning opportunities.

In addition, individuals who hold a growth mindset appreciate both positive and negative feedback and treat all errors as important lessons to grow (Mangels et al., 2006). However, students with a fixed mindset are more prone to negative self-recognition, such as blaming their intelligence for their failure. They tend to avoid difficult tasks that may reveal their limitations (Westby, 2020; Yeager & Dweck, 2012). This avoidance behaviour can hinder students' academic development, especially in mathematics tasks that require perseverance and resilience.

Another possible factor that may contribute to a weaker influence of growth mindset on mathematics for low-achieving students is that a growth mindset alone may not be sufficient to overcome persistent academic challenges. They may require additional remediation to support and strengthen their basic skills. A study by Huillery et al. (2021) supported this, highlighting that low-achieving students may need a more targeted and consistent support beyond just fostering growth mindset. However, these are interpretations that require empirical testing in future research. Further investigation was required to determine how a growth mindset can be most effectively combined with other interventions to enhance learning for low-achieving students. In addition to examining these combinations, future research could also explore the mediating variables that explain the interaction between growth mindset and mathematics achievement. These potential and emerging mediating variables include metacognitive skills, reasoning ability, and neurophysiological mechanisms.

LIMITATIONS AND CONCLUSION

This study was limited to Grade 7 students in Kota Kinabalu, Sabah. Other states in Malaysia may show different results with respondents from various socioeconomic and cultural backgrounds. Therefore, the results may not generalise to other places in Malaysia. So, further investigation should be conducted in other places in Malaysia to make a general conclusion. In addition, this study used a cross-sectional design with a correlational design. Future research can use a longitudinal design to investigate the causes of growth mindset effect on mathematics achievement. They can also triangulate the results through qualitative analysis, such as interviews with teachers and students, to obtain a deeper understanding of the issue. In addition, although other countries such as the United States and China have shown that a growth mindset can significantly improve students' motivation and academic performance, it is still relatively new in Malaysia. Thus, more local research is needed to validate these findings within the Malaysian context.

In conclusion, growth mindset was positively correlated with the students' overall mathematics achievement. However, the quantile regression analysis indicates that it has a more substantial effect on high-performing students than low-performing ones. Growth mindset still benefits low-performing students despite the low effect. They may need additional support, such as a remedial class, to boost the growth mindset effect in fostering their foundational skills in mathematics.

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APPENDIX

Item code	Item statement
B1	How well I do in mathematics test is something that I cannot change very much.
B2	I can learn new topic in mathematics, but I cannot really change my performance in mathematics test.
B3	I cannot always get much better at mathematics, no matter how well I do in test.