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Modeling cognitive and non-cognitive factors that influence students' reading achievement in Saudi Arabia: A structural equation modeling analysis of PISA (2018)

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ABSTRACT

Reading is essential at all educational levels. This study explores factors influencing reading achievement among Saudi students, using structural equation modeling (SEM) based on PISA 2018 data. It examines whether students' perceptions of teacher support enhance reading skills by promoting self-efficacy and a sense of belonging. Results show that perceived teacher support does not directly affect reading interest (p-value = 0.868). However, self-efficacy and a sense of belonging fully mediate the relationship between teacher support and reading interest. Positive correlations were found between teacher support, self-efficacy, a sense of belonging, and reading ability (p-value = 0.001). This research offers insights into Saudi Arabia's educational context and can inform future studies in similar educational systems.

1. Introduction

Structural equation modeling (SEM) is widely recognized for its versatility in analyzing diverse data types, research designs, and theoretical models, making it one of the most prominent statistical techniques (Schreiber et al., 2006; Schreiber, 2008). SEM allows researchers to explore intricate connections between observed and latent variables, revealing direct and indirect relationships between latent variables, which are indirectly measured through the associations with observed variables (Civelek, 2018).

In recent years, SEM has been widely employed in several fields, including psychological research, sociology, and economics (MacCallum and Austin, 2000). Heinen et al. (2017) used SEM in the study of 321 first-year medical students to determine the relationships between emotional discomfort (anxiety and depression) and perceived stress while accounting for the activation of personal resources (resilient coping, self-efficacy, and optimism). Using SEM, Guilherme et al. (2022) measured geographical and environmental factors' direct and indirect impacts on ant beta diversity throughout the Amazon basin. Özüdoğru (2022) applied SEM to investigate the relationships among distance education classroom environment variables and course achievement. Xue et al. (2023) used SEM to evaluate the relationship between a healthy work environment and work engagement while considering the impact of psychological capital on intensive care unit nurses.

Saudi Arabia's education sector is going through a significant transformation, focusing on enhancing the quality of schooling. It has established quality assurance standards for all educational settings and provides teachers and principals with the necessary resources and training to support student learning. The governance of the education system plays a crucial role in shaping the vision, objectives, and strategies for improving educational outcomes. Aligned with Vision 2030, Saudi Arabia aims to create a highly skilled and talented community by prioritizing education. This will equip students for jobs that have not been created yet, technologies that have not been invented yet, and problems that have not yet emerged (OECD, 2019a). Therefore, Saudi Arabia has decided to evaluate the education sector by participating in standardized assessments such as Trends in International Mathematics and Science Study (TIMSS), the Programme for International Student Assessment (PISA), and the Teaching and Learning International Survey (TALIS).

The Programme for International Student Assessment questionnaire, conducted by The

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Organization for Economic Cooperation and Development (OECD), might raise important considerations for educators in Saudi Arabia. The PISA-based test for schools provides performance estimates at the school level and data from student surveys that gather information about the learning environment and students' attitudes toward learning. The surveys are conducted every three years, focusing on 15-year-old students in participating countries. PISA aims to determine how well students are prepared for future challenges rather than focusing on specific curricula. The subjects assessed in PISA include reading, mathematics, and science. There are 37 OECD member countries and 42 partner countries. While Saudi Arabia has participated in other international assessments, it participated in PISA for the first time in 2018 despite not being a member of the OECD (Mo, 2020). The main subject assessed in PISA 2018 was reading literacy, which involves understanding, using, evaluating, reflecting on, and engaging with texts to achieve goals, develop knowledge, and participate in society (OECD, 2019c). PISA is extensively informative, so many researchers investigate the underlying relationships between different variables in participating countries.

Banat and Pierewan (2019) indicated that international achievement scores demonstrate the importance of reading literacy. For most students, reading literacy is not ingrained in their daily lives. Certain students have not employed reading techniques to enhance their comprehension, which will impact academic performance. While reading ability has been widely acknowledged as a prerequisite for comprehending learning objectives and attaining academic success in most educational settings, it is evident that numerous students face challenges when it comes to reading textbooks (Chang and Bangsri, 2020).

Reading ability: Liu (2010) pointed out that reading ability is a cognitive ability that a person can use when interacting with texts. It is based on analyzing fundamental reading proses, such as tracking text, decoding, and fluency, using eye-tracking data. As students with less reading proficiency tend to choose the simple academic tasks that do not require much effort and perseverance, they will inevitably be less engaged in the reading task and less able to continue achieving it or overcoming its challenges when they lack confidence in their ability to read (Alzubi and Attiat, 2021). One strategy for helping kids become proficient readers is to read books to them or tell them stories. Storytelling helps kids with their fundamental development. It supports the brain, eyes, and ears' sensory development. It also fosters reading habits, memory, and focus, all supporting children's happy learning. Children's confidence, speaking abilities, listening skills, behaviors, and social values will all be enhanced by storytelling (Pongutta et al., 2019; Saksiriphol and Kunchune, 2023).

Self-efficacy: Jungert and Rosander (2010) pointed out that academic self-efficacy, a student's perceived capability to reach explicit academic goals, has been positively linked to a strategy used and self-regulation. Self-efficacy affects the choice of activities, effort, persistence, and achievement. Compared with students who doubt their learning capabilities, those with high self-efficacy for accomplishing a task participate more readily, work harder, persist longer when encountering difficulties, and demonstrate higher achievement (Lam et al., 2012). Self-efficacy is individuals' conviction in their ability to complete their life tasks. Their level of self-efficacy influences student employability (Abdillah et al., 2023). A person's level of self-efficacy influences their propensity to act in certain ways, such as whether or not they take on a task, how much effort they put into it, and how long they endure when faced with challenges and unpleasant experiences (Holzer et al., 2024).

Sense of belonging: Sense of belonging is the psychological feeling of belonging or connectedness to a social, spatial, cultural, professional, or other group or community. A sense of belonging can impact students' motivation, academic performance, and well-being. Also, students' perceptions of their acceptance, worth, diversity, and encouragement from peers and the teacher in the academic classroom, as well as their sense of their significance in the lives and activities of the class (Hurtado and Carter, 1997). Sense of belonging is the "need to form and maintain at least a minimum number of interpersonal relationships" based on love, support, acceptance, and trust. People with a sense of belonging have a sense of acceptance, liking, and relationships with others and a sense of community. For young students, their family is the core of their emotional and social world. In this way, a student's feeling of acceptance, respect, and support in their school's community is reflected in their sense of belonging (OECD, 2019b).

Teacher support: In general education, teacher support research has received much attention (Johnson and Johnson,1983; Malecki and Demaray, 2003; Liu and Li, 2023). Teacher support enhances a teacher's relationship with a student. Specifically, teachers who support students show their care and concern for their students, so these students often reciprocate this concern and respect for the teacher by adhering to classroom norms (Lei et al., 2018).

The present study primarily focuses on examining the influence of perceived teacher support on the reading achievement of Saudi high school students using the PISA 2018 student questionnaire (Mo, 2020). This questionnaire encompasses various aspects, including teacher support, a sense of school belonging, self-efficacy, and students' reading ability. The study's main objective is to investigate whether students' perception of teacher support can positively impact their reading ability, with self-efficacy and a sense of school belonging mediating this relationship. Furthermore, the study hypothesizes that the association between teacher support and reading ability will remain consistent for both male and female students. The research findings carry significant implications for educators, policymakers, and practitioners, as they offer valuable insights into effective strategies for enhancing reading achievement in Saudi Arabia.

1.1. Research objective

1. Identify the latent variables affecting the students' reading achievement in the education sector in Saudi Arabia.
2. Apply SEM to investigate the interrelationship between observed and latent variables in PISA in Saudi Arabia.
3. Examine the effect of teacher support on reading ability as a cognitive construct through self-efficacy and a sense of school belonging, which are both non-cognitive constructs.

1.2. Importance of research

The research has several anticipated benefits. Firstly, it utilizes advanced statistical methods to analyze complex relationships between factors influencing students' reading achievement. It will contribute to the field of education by providing a reference for applied multivariate statistical techniques.

Secondly, the research can validate and support existing education theories while incorporating the best practices from related studies. Therefore, testing the proposed direct relationships between independent and dependent variables and exploring indirect or mediated relationships through observed and latent variables is crucial. Since Saudi Arabia participated in PISA 2018 for the first time, this study will serve as a valuable reference for analyzing students' reading achievement in Saudi Arabia. Moreover, as data from Saudi Arabia had not been analyzed before, this research is the first to employ SEM based on data from PISA 2018 in Saudi Arabia (Mo, 2020). The research paper is structured as follows: Section 2 provides a comprehensive literature review, Section 3 explains the models and methodology employed in this study, Section 4 presents the data analysis and results, and finally, Section 5 presents clear findings derived from the analysis and concludes the study.

2. Literature review

According to McCoach (2003), SEM was used to investigate the relationship between creativity, IQ, and academic achievement. Kusurkar et al. (2013) conducted a study on 383 medical students and utilized SEM to examine the relationship between academic performance, study strategies, study effort, and relative autonomous motivation. They discovered a positive correlation between academic performance, deep study strategies, and higher study effort. Additionally, they found that relative autonomous motivation was positively associated with effective study strategies, which, in turn, was linked to increased study effort. Zhao and Chang (2019) explored the impact of various factors, including students' family socioeconomic status, gender, family support, learning motivation, peer relationships, and teachers' equity, on the occurrence of school bullying in Hong Kong. The data used for analysis is derived from the PISA 2015 survey. Furthermore, the study employed SEM, and the findings suggest that family support, peer relationships, and teacher fairness negatively influence school bullying (Mora-Ruano et al., 2021).

In contrast, scientific reasoning skills directly impacted content knowledge learning gains, but cognitive skills had no such effect. Confirmatory factor analysis and SEM are used in Sweden's TIMSS 2015 (Trends in International Mathematics and Science Study) data. The findings show a strong correlation between teacher job satisfaction and schoolwork conditions. More precisely, workload, cooperation, and judgments of student discipline in the classroom were strongly correlated with job satisfaction (Toropova et al., 2021). Fauzan et al. (2023) employed SEM to investigate the influence of internship experience and work motivation on student’s work readiness in vocational education.

Li (2011) applied SEM on PISA 2006 to assess the science achievement of Turkish students. The analysis aimed to identify the variables that influenced science achievement and examine their relationships with other variables. The results revealed that time was the most significant factor influencing the achievement, surpassing factors like the environment, education, and attitudes. The study conducted by Bulut et al. (2012) applied SEM on PISA 2009 investigated the relationship between students' attitudes toward reading, self-regulation, and the use of technology for reading. Furthermore, the study demonstrated that self-regulation indirectly influences reading scores by influencing attitudes toward reading and using technology for reading purposes. Lezhnina and Kismihók (2022) utilized statistical and machine-learning techniques to examine how German students' attitudes toward information and communication technology (ICT) in relation to mathematical and scientific literacy, as measured by the Programme for International Student Assessment (PISA) in 2015 and 2018. They employed Hierarchical linear models (HLM) to explore the complex relationships between ICT attitudes and mathematical/scientific literacy, considering the hierarchical structure of the data. HLM results suggest that ICT autonomy could significantly impact mathematics and science, thus warranting further investigation. Koyuncu et al. (2022) examined the moderating influence of gender and socioeconomic status factors on the relationship between students' metacognitive skills and reading performance using SEM with PISA 2018 Turkish students.

Relationships between perceived teacher support, sense of belonging, and reading ability: According to Uysal (2015), SEM was employed in a study that found a moderate and positive correlation between a student's mathematics achievement, their interest in mathematics, and their self-concept in mathematics. The study also found that mathematics anxiety negatively and moderately impacts mathematics achievement. However, an insignificant relationship was found between teacher-student relationships, classroom management, sense of belonging, and mathematics achievement among Turkish students in the PISA 2012 assessment. Johansson and Myrberg (2019) examined the correlation between the reading performance of fourth-grade students, the specialization of their teachers, and the student's perception of the quality of instruction. The study utilized data from the Swedish PIRLS 2011 survey. It employed SEM to uncover a positive association between teacher specialization in the specific grade and subject being taught and the student's reading achievement.

Simultaneously, the TALIS 2013 and PISA 2012 surveys found that a triangulated approach to school strategy, which emphasizes enhancing teacher participation, principal commitment, and school responsibility, correlates significantly with student performance by SEM (Huang et al., 2019). Chang and Bangsri (2020) utilized SEM techniques to analyze PISA 2018 data in Thai. The results revealed that the perceived teacher support among Thai high school students indirectly impacted their reading ability, mediated by their self-efficacy and sense of school belonging. He indicated that students spend up to 20,000 hours in classrooms per year; other factors can affect students' academic performance and ability to apply knowledge in real life. A sense of belonging is essential to a college student's academic success and retention, particularly at disadvantaged institutions of higher learning, such as private colleges in China. Analysis using SEM has shown that first-year students' sense of belonging and ability to control their emotions are significantly positively correlated. Specifically, emotion regulation moderates the relationships between student's happiness, sense of achievement, college satisfaction, and belonging (Tian et al., 2021).

According to Mora-Ruano et al. (2021), the data from German PISA 2015 used SEM to estimate the direct impacts of instructional leadership on teacher collaboration and teacher collaboration on student achievement, as well as the indirect effects of instructional leadership on student achievement. Pamularsih (2022) indicated that disruptive behavior in Indonesian students was the most significant negative influence on reading achievements in the PISA 2018 assessment using SEM.

Relationships between perceived teacher support, self-efficacy, and reading ability: Albayrak Sari (2015) used SEM to determine the factors that affect reading skills. He found that teaching strategies were the most important latent variables that affected the student's reading comprehension skills. In addition, the least effect was the student's attitude toward reading. The Teaching and Learning International Survey (TALIS), a global teacher survey, was used to gather research data. The self-efficacy model of Ukrainian teachers using SEM methodology was examined. It was demonstrated that Ukrainian teachers had lower levels of self-efficacy. Moreira-Fontán et al. (2019) tested the structural model and showed that all variables related to information and communication technologies (ICT) significantly predicted autonomous motivation. Krüger and Formichella (2019) examined the hypothesis that cognitive -knowledge and skills- and non-cognitive -attitudes competencies mediate between the traditional explanatory factors incorporated in the education production function and the cognitive outcomes. They estimated a structural equations model using PISA 2012 data in Argentina. Navarro-Mateu et al. (2020) applied SEM to investigate how self-efficacy and emotional intelligence influence students' stress. The self-efficacy factor is commonly used in curriculum and demographic frameworks. The partial least square structural equation modeling (PLS-SEM) method was used to examine the fact that self-efficacy scales have been used widely across the curriculum and demographic structures in the Malaysian context (Mohd Dzin and Lay, 2021). Dadandı and Dadandı (2022) found that teacher behaviors that support students' reading engagement, enjoyment, and self-efficacy strongly impact reading achievement when SEM is applied to PISA 2018 data in Turkey.

Fereydouni et al. (2022) noted that the structural equation model was used to examine the impact of self-efficacy and self-care on quality of life.

The study conducted by Chuang et al. (2022) integrated career construction theory and self-determination theory to develop a model that examines the connection between the "motivation," "self-efficacy," "fear of failure," "career adaptability," and "meaning in life" among vocational school students. The researchers utilized PISA 2018 data in Taiwan and validated the model through the partial least squares structural equation model (PLS-SEM).

Saudi Arabia is dedicated to creating a highly skilled society and greatly emphasizes education as a core element of its Vision 2030. This study is important to strategic planners in Saudi Arabia and global audiences interested in understanding the country's educational goals. Saudi Arabia is recommended to establish comprehensive standards for quality assurance in all educational settings and provide teachers and principals with the necessary resources and training to facilitate effective student learning. The governance of the school system, encompassing the vision, rationale, implementation, and desired outcomes, plays a critical role in accomplishing educational objectives. The current plans in Saudi Arabia align with international best practices, and various levels of government have taken responsibility for achieving the educational vision (Mo, 2020).

The OECD has published results about descriptive statistics and linear regression analysis related to

Saudi Arabia's PISA 2018. Furthermore, a study on SEM was absent from Saudi Arabia in the 2018 PISA. While SEM has been employed in other countries, its application in PISA 2018 in Saudi Arabia's educational system is yet to be explored. This research addresses this gap and utilizes the SEM procedure to investigate the cognitive and non-cognitive factors influencing reading achievement. Using SEM, a more comprehensive approach can be adopted to analyze these constructs' complex relationships and impact on reading achievement within Saudi Arabia's educational system. The findings of this thesis will greatly contribute to the existing knowledge gaps and provide valuable insights for policymakers and educators. Furthermore, this research will advance educational research and catalyze future studies. We anticipate this research will support our hypothesis, which incorporates various psychological characteristics related to schooling, particularly in PISA 2021.

3. Methodology

This study is based on the public database of the PISA 2018 (OECD) questionnaire, which mainly focused on reading.

The study measured all observed variables on a four-point Likert scale, ranging from 1 (strongly disagree) to 4 (strongly agree). Self-efficacy, a latent variable, was defined using five questions. Reading ability, another latent variable, was defined using three questions from the student's reading self-assessment. The sense of school belonging, also a latent variable, included a total of six questions and was split into two categories: positive and negative senses of belonging. Lastly, the latent variable of teacher support was measured using four questions, as shown in Table 1.

SEM is a form of causal modeling and a theory-driven confirmatory approach. It starts by specifying a theoretical model based on theory from the literature. SEM commonly includes two types of models: structural models and measurement models. The measurement model establishes a relationship between the observed and latent variables, while the structural model establishes a relationship between the latent variables (Iacobucci, 2009). Confirmatory factor analysis (CFA), part of SEM, is a technique used to analyze the efficacy of the measurement model and the specified direct relationships (Hair et al., 2006).

Table 1: Factors and variables description

Factors	Variables	Questions
Sense of school belonging (SOB)	NSOB Q1	Thinking about your school: I feel like an outsider (or left out of things) at school
	NSOB Q2	Thinking about your school: I feel awkward and out of place in my school
	NSOB Q3	Thinking about your school: I feel lonely at school
	PSOB Q1	Thinking about your school: I make friends easily at school
	PSOB Q2	Thinking about your school: I feel like I belong at school
	PSOB Q3	Thinking about your school: Other students seem to like me
Self-efficacy (SE)	SE Q1	I usually manage one way or another
	SE Q2	I feel proud that I have accomplished things
	SE Q3	I feel that I can handle many things at a time
	SE Q4	My belief in myself gets me through hard times
	SE Q5	When I'm in a difficult situation, I can usually find my way out of it
Teacher support (TS)	TS Q1	How often: The teacher shows an interest in every student's learning
	TS Q2	How often: The teacher gives extra help when students need it
	TS Q3	How often: The teacher helps students with their learning
	TS Q4	How often: The teacher continues teaching until the students understand
Reading ability (RA)	RA Q1	I am a good reader
	RA Q2	I am able to understand difficult texts
	RA Q3	I read fluently

NSOB: Negative sense of school belonging; PSOB: Positive sense of school belonging

As Marsh et al. (2014) mentioned, SEM, like regression analysis, requires certain assumptions and data characteristics. However, SEM utilizes multiple regression concepts within the structural or measurement model. As a result, the assumptions underlying regression models remain applicable to structural equation models. These assumptions, including linearity, normality, absence of multicollinearity, and homoscedasticity, play a fundamental role in effectively implementing SEM. In addition, data should be checked for possible coding mistakes, missing values, and outliers (Civelek, 2018). According to Collier (2020), the indicator's series mean is the most common imputation method to replace the missing value. Severe outliers can cause deviation from normality data distribution; hence, examining and handling outliers are important to meet the normality assumption for maximum likelihood estimation. The Mahalanobis D^2 measure, a multivariate assessment of each observation among variables, will be used in our research. The D^2/df measure's threshold levels should be conservative (0.005 or 0.00001), resulting in 2.5 (small samples) against 3 or 4 (larger samples) being used as the threshold value for designation as an outlier (Hair et al., 2006). Skewness and kurtosis values and the difference between trimmed mean and mean were checked as indicators of normality (Karakaya-Ozyer and Aksu-Dunya, 2018). According to Collier (2020), if the coefficient of skewness falls between -2 and +2, the data can still be considered normal. Based on kurtosis, a range of -10 to +10 determines if the distribution is normal. Another important factor to consider is the absence of multicollinearity, which means that independent variables should not be correlated (Civelek, 2018). It is also crucial to have homoscedasticity, which means there should be no relationship between independent variables and error terms (Marsh et al., 2014). The recommended sample size for SEM is at least 200 participants (Gazeloglu and Greenacre, 2020). Lastly, in the structural equation model, it is assumed that there are linear relationships between latent and observed variables (Marsh et al., 2014).

Exploratory factor analysis was used to identify factors based on the relationships between variables, allowing observed variables to load on multiple factors. On the other hand, CFA was used to validate a pre-determined factor structure by confirming that factors load onto observed variables as predicted (Marsh et al., 2014).

3.1. Exploratory factor analysis

Exploratory factor analysis (EFA) was used to compare the reliability coefficients calculated in this study with those published by the OECD in the PISA 2018 report. The primary objective of EFA is to reduce the dimensionality of the original data and gain a meaningful understanding of the new space, represented by a smaller number of new dimensions. The EFA coefficients were evaluated and reported at the country and international levels. By analyzing the correlation matrix of the variables under study, EFA assists in identifying variables that have strong intercorrelations, allowing them to be grouped as indicators of a shared underlying factor (Finch, 2013). Several approaches are available to assess the EFA model adequacy, including the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO-test). The sample size is considered adequate if the value of KMO is greater than 0.5. Bartlett's test of sphericity is a statistical test for assessing the overall significance of the correlation matrix. This test will be significant if the determinant is greater than 0.00001. If the test is insignificant, remove the observed variables that cause scattered correlation models from the analysis and perform factor analysis again (Finch, 2013).

Addressing the reliability and validity of instruments is crucial as they determine the consistency and accuracy of measurements for a latent variable. The reliability coefficient, commonly measured by Cronbach's alpha, assesses the overall consistency of all the observed variables. A commonly accepted lower limit for Cronbach's alpha is 0.70, which may be reduced to 0.60 in exploratory studies. To improve reliability, a potential solution is to systematically remove variables below the threshold one by one (Hair et al., 2006). Conversely, validity refers to how accurately a set of measures represents the concept of interest. Convergent and discriminant validity are widely recognized as the most accepted forms of validity. Convergent validity assesses the degree to which two measures of the same concept correlate. High correlations indicate that the observed variable is measuring its intended concept. From the factor matrix, we might determine that variables with the same factor as expected are grouped into a single factor. It is expected to have a loading of 0.3 or above significant only for sample sizes of 350 or greater between the latent and observed variables (Hair et al., 2006). If there are cross-loadings, which means observed variables loading on different latent variables, the differences between these loadings should be greater than 0.2. To fix the convergent validity issues, we might remove the items with the worst cross-loadings one at a time. Alternatively, these factors could be two or more dimensions of a higher-order factor (Hair et al., 2006). Discriminant validity is the degree to which two conceptually similar concepts are distinct. The summated scale should have a low correlation with similar concepts, indicating that the summated scale differs adequately from similar concepts. The initial step in diagnosing is to look at the pattern matrix, which shows which variables should be significantly loaded on only one factor. Examining the factor correlation matrix is the second method. The factor correlations should not exceed 0.70. Resolving this issue requires a separate EFA with just the items from the offending factors (Hair et al., 2006).

3.2. CFA

CFA is utilized to conduct a confirmatory test on measurement theory, supporting or refuting our initial assumptions in exploratory factor analysis. Measurement theory outlines how observed variables accurately and systematically depict the factors present in a theoretical model (Thompson, 2004). The measurement model of SEM is a CFA. The objective of CFA is to test the reliability of the observed variables and provide a rigorous convergent and discriminant validity test. In addition, the measurement model examines the extent of interrelationships and covariation among the latent variables. As part of the process, factor loadings, unique variances, and modification indices are estimated to derive the best variables of latent variables before testing a structural model (Hair et al., 2006). It is important to check the CFA model's adequacy before conducting SEM, which can be checked using reliability, convergent validity, discriminant validity, and model fit.

Composite reliability (CR), also called Raykov's Rho (r), is a measure of the reliability and internal consistency of the observed variables that represent a latent variable (Hair et al., 2006). Composite reliability has the same range and cutoff criteria as Cronbach's alpha for an acceptable level of reliability of 0.70 (Collier, 2020). It can be computed from the squared sum of factor loadings (L_i) for each factor and the sum of the error variance terms for a factor (e_i) as shown in Eq. 1. To fix the reliability issues (i.e., <0.70), variables less than the threshold should be removed one by one (Hair et al., 2006).

$$CR = \frac{(\sum_{i=1}^{n} L_i)^2}{(\sum_{i=1}^{n} L_i)^2 + (\sum_{i=1}^{n} e_i)} \quad (1)$$

Convergent validity refers to the degree to which different observed variables that measure the same construct align. Various methods can be employed to assess convergent validity among these observed variables, including examining factor loadings and calculating the Average Variance Extracted (AVE). The AVE is computed by taking the mean of the variances extracted for the observed variables that load onto a specific factor, serving as a general indicator of convergence, as depicted in Eq. 2 (Hair et al., 2006). Typically, a guideline aims for standardized factor loading estimates of 0.5 or above, whereas the ideal value based on the literature is 0.7 or higher (Hair et al., 2006).

$$AVE = \frac{\sum_{i=1}^{n} L_i^2}{n} \tag{2}$$

The L_i Represents the standardized factor loading, and i is the number of variables. So, for n variables. On the other hand, an AVE of less than 0.5 indicates that, on average, more error remains in the variables than the variance explained by the factor structure imposed on the measure. We could remove observed variables less than the threshold one by one to fix this issue and then recalculate the AVE until we achieve a good rule of thumb (Hair et al., 2006).

Discriminant validity refers to the degree to which a factor is distinct from others. In CFA, two common approaches exist for evaluating discriminant validity. One approach involves setting the correlation between any two factors equal to one. In contrast, the other approach compares the average variance-extracted values for two factors with the square of their correlation estimate. The squared correlation estimate should be more statistically significant than the variance extracted estimates to demonstrate discriminant validity. The presence of cross-loadings indicates a problem with discriminant validity. To address this issue, one can modify the model so that each observed variable is only an indicator of one latent variable. The difference in fit between the original and modified models would indicate whether the objects represent different factors (Asabuwa Ngwabebhoh et al., 2020).

The model fit test determines how well the model's overall structure fits the data. A good model fit does not imply that every aspect of the model is well-fitting. The total model is compared to the data to determine model fit. There are more than 20 model fit tests, but we will discuss only the prominent ones seen in most research, as presented in Table 2 (Kline, 2015).

Modification indices (MI) are part of the analysis and valuable tools as they provide insights into potential alterations and suggest model alterations to achieve a better fit (Hair et al., 2006). In this context, a reduction in the $chi-square/df$ ratio is used to measure the improved fit. Generally, χ^2/df smaller than two are considered highly desirable, while values between 2 and 5 are deemed acceptable (Asabuwa Ngwabebhoh et al., 2020). Modification indices are estimated for all non-estimated parameters, so they are generally provided for diagnosing error term correlations only within the same construct and correlational relationships between constructs that may not be initially specified in the CFA model one at a time (Hair et al., 2006).

Table 2: Cutoff criteria for several fit indices

Indices	Shorthand	Rule of thumb
Absolute/predictive fit		
Goodness-of-fit index	GFI	≥ 0.90
Adjusted GFI	AGFI	≥ 0.90
Root means a square error of approximation	RMSEA	< 0.06
Standardized root means square residual	SRMR	< 0.06
Incremental fit measures		
Normed fit index	NFI	≥ 0.90 for acceptance
Incremental fit index	IFI	≥ 0.90 for acceptance
Tucker–Lewis index	TLI	≥ 0.90 for acceptance
Comparative fit index	CFI	≥ 0.90 for acceptance
Parsimonious fit		
Parsimony-adjusted NFI	PNFI	≥ 0.50
Chisq/df	$\frac{\chi^2}{df}$	$\frac{\chi^2}{df} \leq 2$ or 3

Measurement model invariance across groups is crucial in comparing and interpreting data across different groups or time points. The assessment of measurement invariance involves several steps. The first step is to evaluate configural invariance, which tests whether the constructs possess the same pattern of loadings across groups or time points. This step checks if the loadings on the latent variable are consistent for all groups being compared. If configural invariance is supported, the next step is to examine metric invariance. This step ensures that the items within the construct contribute similarly to the latent variable across groups. The factor loadings are constrained to be equivalent across different groups to establish metric invariance. Once metric invariance is confirmed, the final step is to assess scalar invariance, ensuring that the items' shared variance accurately captures any mean differences in the construct across groups. Scalar invariance is achieved by constraining the item intercepts to be equivalent across groups. If all three types of measurement invariance (configural, metric, and scalar) are upheld, it indicates that the construct has the same structure and meaning across groups or time points. This allows for meaningful comparisons and valid conclusions (Putnick and Bornstein, 2016).

The model fit criteria used for each test of invariance were recorded, including change in chi-square ($\Delta\chi^2$), change (ΔIFI), including (ΔCFI), (ΔRMSEA), (ΔSRMR), and (ΔTLI) (Putnick and Bornstein, 2016). Based on Cheung and Rensvold (2002), the difference in the Tucker–Lewis Index (TLI), Incremental Fit Index (IFI), and normed fit index (NFI) should be less than or equal to 0.05, which it will use (Putnick and Bornstein, 2016).

Common method bias (CMB) refers to the degree to which correlations are altered or inflated due to a method's effect. Including a common method factor in the CFA is widely recognized as one of the most popular methods for addressing common method bias. A common method factor is a latent variable directly related to each factor. To detect this issue, we will perform a chi-square difference test to determine if bias is present between the results of CFA with no common method factor included and the results of CFA with a common method factor included. In the analysis, we need to observe a difference of 1 degree of freedom (df) between the two models. The critical value for significance with one df is 3.84 at $p-value=0.05$. Suppose the difference between the models exceeds this value. In that case, it indicates the presence of CMB, i.e., if the chi-square difference is statistically significant, it suggests the presence of a common method bias (CMB). To fix the common method bias issue, i.e., common method bias is significant, it must have the common method factor and its relationships to all the observed variables when testing the structural relationships between factors (Collier, 2020). If the common method bias test yields an insignificant result, it suggests no evidence of bias in the data. Therefore, the structural analysis may not need to include the common method factor.

The second-order CFA model involves latent variables that measure a higher-order factor. In CFA, these higher-order factors are extracted while keeping the factor covariances/correlations fixed at zero (Collier, 2020). To test the assumption that one or more higher-order factors can account for the correlations among a set of first-order factors (Brown, 2015).

Brown (2015) suggested a general strategy for testing second-order or higher-order factor models:

1. Start by developing a well-defined first-order CFA model that aligns with the study's conceptual framework.
2. Evaluate the correlations among the first-order factors to assess if it is reasonable to hypothesize that a second-order factor can explain their associations.
3. Test the fit of the higher-order factor model and assess its conceptual validity.

3.3. SEM

SEM refers to a group of associated methods rather than a specific statistical process (Kline, 2015). Variance-Based Structural Equation Modeling (VB-SEM) and Covariance-Based Structural Equation Modeling (CB-SEM) are two types of SEM. Two approaches used by VB-SEM and CB-SEM, nonparametric and parametric testing, are entirely different, as cited in Awang et al. (2015). Unlike the nonparametric processes in VB-SEM, the parametric procedures in CB-SEM are based on assumptions such as adequate sample size and normally distributed data (Awang et al., 2015).

SEM, in comparison with CFA, expands the potential for connections between the underlying variables and consists of two main components: (a) a measurement model, which is essentially the CFA, and (b) a structural model. as shown in Fig. 1. In addition to the new terms, two other terms are associated with SEM: exogenous, similar to independent variables, and endogenous, similar to dependent or outcome variables (Schreiber et al., 2006).

Steps for conducting SEM analysis: The actual SEM analysis consists of five sequential steps: model specification, model identification, model estimation, model testing, and model modification, as shown in Fig. 2.

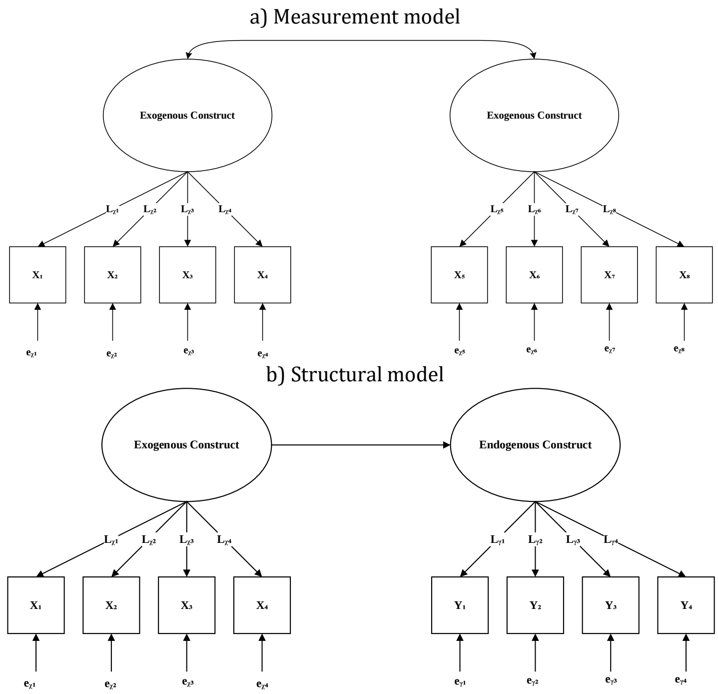

Fig. 1: Measurement and structural model relationships in a simple SEM model (Hair et al., 2006)

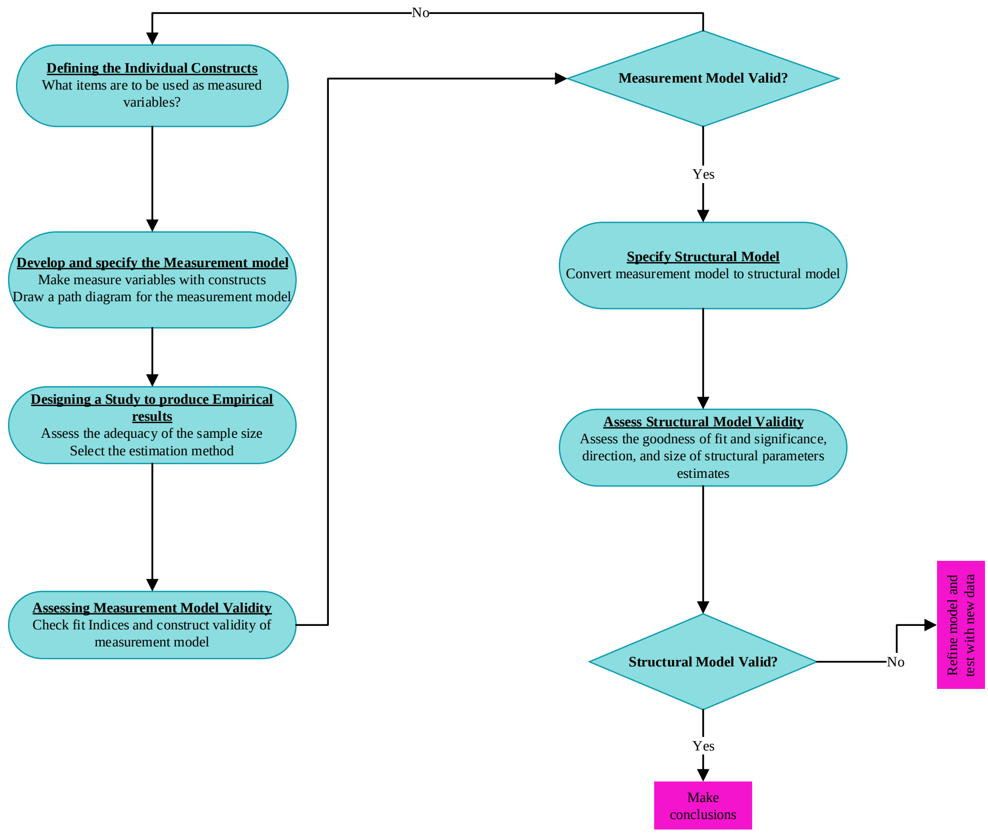

Fig. 2: Flowchart of the basic steps of the SEM model (Hair et al., 2006)

Model specification: In this step, a theoretical model is specified to identify the latent and observed variables of interest and their relationships using relevant, related theory and research. In this step, the researcher must select a measurement and structural model (Williams et al., 2010).

Model identification: This step helps the researcher determine whether the specified model can produce actual results that can be estimated in SEM analysis. Models must be identifiable, able to produce a singular solution, and can estimate parameters (Crockett, 2012).

Model estimation: This step involves assessing how well the model fits the data, meaning how accurately it represents the data patterns. The most common methods used for this are Maximum Likelihood (ML) and Generalized Least Squares (GLS) (Crockett, 2012).

- Interpretation of the parameter estimates.
- Consider equivalent or near-equivalent models (Kline, 2015).

Model testing: Before testing the structural model, we should conduct a CFA of the measurement model to determine whether the observed variables are loaded on the latent variables in the expected direction. To evaluate the fit between the theoretical model and the sample data, it is important to assess multiple fit indices from different categories: absolute, comparative, and parsimonious. It is crucial to note that the measurement model must exhibit a strong fit to the data before analyzing the structural model (Crockett, 2012). The comparative fit index (CFI), Tucker-Lewis index (TLI), and Root mean square error of approximation (RMSEA) are common fit indices for SEM analysis. The Chi-square value and degrees of freedom are commonly reported; they are not usually relied upon to support the goodness of fit between data and a model. This is because the size of the sample can influence the Chi-square value. When the sample size is large, even if the data fits the model well, the Chi-square value will still statistically significantly differ from 0 (Schreiber, 2008). Like CFA, model fit indices will be used with the same concept.

Model modification: Based on the fit indexes, the decision is made to keep, modify, or respecify the model and repeat the analysis. After the modifications are made, it is important to acknowledge that the analysis has moved from confirmatory to exploratory. Researchers often respecify or modify the original model when parameter estimates are statistically nonsignificant (Schreiber, 2008). Reporting the results: The final step entails accurately describing the analysis in written reports (Kline, 2015).

3.3.1. Mediation and moderation

In mediation analysis, we examine a mediator variable that assists in understanding the mechanism through which an independent variable impacts a particular outcome (Kline, 2015). Mediation is about identifying how and why an indirect effect occurs. Moderation analysis involves exploring the circumstances in which the relationship between two variables is pronounced.

Both mediation and moderation analyses serve to examine the causal relationship between variables. Mediation focuses on understanding the mechanisms and reasons behind an effect. At the same time, moderation seeks to uncover the specific conditions or contexts in which an effect occurs, such as differences between boys and girls or before and after a certain event. Moderation works like measurement invariance but in the context of SEM. We assess measurement invariance through moderation, as discussed in the concept of measurement invariance (Kline, 2015).

4. Results and discussion

4.1. Data screening

The dataset contains 18 observed variables. The subjects-to-item ratio is calculated as 10 multiplied by 18, resulting in a ratio of 180. The sample size consists of 6136 cases, considered adequate according to (Gazeloglu and Greenacre, 2020). Missing data analysis was performed to identify any missing values for each variable. The imputation by series mean method, a commonly used imputation technique, was applied to replace the missing values.

The correlation coefficients in Table 3 were examined for multicollinearity; no relationships were above 0.7; hence, no multicollinearity issue was found, meaning independent variables are unrelated.

Table 3: Pearson's correlation coefficients

Factors	1	2	3	4	5
1	1.000	0.145	0.214	0.552	0.466
2	0.145	1.000	0.183	0.134	0.170
3	0.214	0.183	1.000	0.185	0.367
4	0.552	0.134	0.185	1.000	0.294
5	0.466	0.170	0.367	0.294	1.000

To detect multivariate outliers, we calculated it is the squared Mahalanobis distance, D_M^2, the calculation of the D^2/df values (df = 123) with the sample having only 6136 observations, a threshold value of 4 was used in large samples, resulting in no observations exceeding the threshold.

Table 4 shows the kurtosis and skewness values for the 18 observed variables. The data are skewed but below an absolute value of 2, so ML estimation with robust standard errors was used. The kurtosis values fall within an acceptable range, indicating they meet the criteria for being considered normal.

4.2. Exploratory factor analysis

In this study, EFA was used to compare the reliability estimates obtained from the data with those reported in the PISA 2018 report by OECD, which evaluated and reported reliability at the national and international levels. The results indicated that the reliability values for each latent variable were consistent with those presented in the PISA 2018 report, except for the sense of belonging variable. The reliability coefficient for this variable was found to be ∝ = 0.351, lower than the threshold. This discrepancy was attributed to the inclusion of negatively and positively worded questions in measuring the sense of belonging. To address this issue, the coding of the sense of belonging variables was reversed to ensure an acceptable level of alpha Cronbach's reliability coefficient.

Table 4: Outputs of kurtosis and skewness

Variables	Skewness values	Kurtosis values
NSOB Q1	1.457	0.931
PSOB Q1	1.389	0.802
PSOB Q2	1.949	2.852
NSOB Q2	1.672	1.725
PSOB Q3	-0.946	0.707
NSOB Q3	-0.432	-0.09
SE Q1	-0.825	0.486
SE Q2	-0.95	1.085
SE Q3	-1.084	1.075
SE Q4	-0.541	-0.208
SE Q5	-1.129	0.968
TS Q1	-0.783	0.358
TS Q2	0.854	-0.069
TS Q3	0.57	-0.263
TS Q4	0.586	-0.246
RA Q1	-0.925	0.217
RA Q2	0.816	1.097
RA Q3	1.165	0.541

Reliability results are summarized in Table 5. The reliability exceeds the acceptable criterion of 0.70.

Two criteria were used to determine the number of factors to be retained for interpretation: eigenvalues and scree plots. First, we applied an orthogonal (VARIMAX) rotation, and the extraction method was the principal component analysis without choosing a fixed number of factors. We employed eigenvalues as a valuable aid in determining the optimal number of factors. We have five factors with an eigenvalue greater than one, which accounts for 63.592% of the overall variance observed in the 18 variables, as presented in Table 6. The rotated component matrix is represented in Table 7, demonstrating that each variable has a noteworthy loading, where a loading above 0.30 is considered significant. The first factor indicates the self-efficacy construct, the second factor represents the teacher support construct, the third reflects a negative sense of belonging, and the fourth corresponds to reading ability. The fifth factor represents a positive sense of belonging. Furthermore, all loadings between the observed variables and factors were above 0.3. As a result, we have successfully established convergent validity.

Fig. 3 shows the breaking point of the scree plot at five factors.

Table 5: Reliability statistics

Factors	No. of observed variables	Cronbach's alpha
Self-efficacy	5	0.808
Teacher support	4	0.826
Reading ability	3	0.750
Sense of school belonging	6	0.725

Table 6: Initial eigenvalues factor analysis

Component	Initial Eigenvalues		
	Total	Percent of variance	Cumulative (%)
1	4.556	25.311	25.311
2	2.495	13.861	39.172
3	1.820	10.109	49.281
4	1.395	7.747	57.028
5	1.182	6.564	63.592

Table 7: Rotated component matrix

Questions	Component				
	1	2	3	4	5
Agree: My belief in myself gets me through hard times	0.736				
Agree: I feel that I can handle many things at a time	0.735				
Agree: I usually manage one way or another	0.715				
Agree: I feel proud that I have accomplished things	0.714				
Agree: When I'm in a difficult situation, I can usually find my way out of it	0.707				
How often: The teacher shows an interest in every student's learning		0.838			
How often: The teacher gives extra help when students need it		0.810			
How often: The teacher continues teaching until the students understand		0.805			
How often: The teacher helps students with their learning		0.778			
How often: Thinking about your school: I feel lonely at school			0.813		
How often: Thinking about your school: I feel awkward and out of place in my school			0.797		
How often: Thinking about your school: I feel like an outsider (or left out of things) at school			0.776		
Agree: I am a good reader				0.794	
Agree: I read fluently				0.786	
Agree: I am able to understand difficult texts				0.772	
Thinking about your school: I make friends easily at school					0.808
Thinking about your school: Other students seem to like me					0.753
Thinking about your school: I feel like I belong at school					0.734

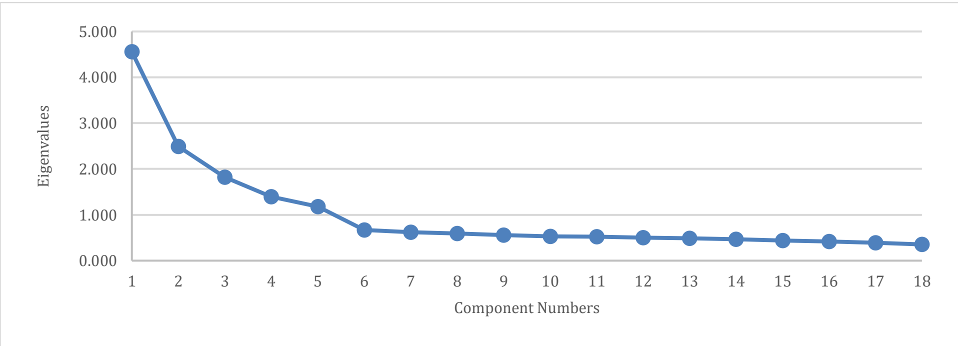

Fig. 3: Scree plot

Table 8 indicates an adequate sample size since the Kaiser—Meyer—Olkin (KMO) measure was 0.848. The Bartlett test of sphericity yields a statistically significant result with a significance level (p-value$\leq$ 0.0001), as presented in Table 8. The correlation between the observed and all other variables, commonality, was in the range of (0.528 and 0.720), indicating a significant correlation. If communalities for a particular variable are low, between 0.0 - 0.4, then that variable may struggle to load significantly on any factor (Collier, 2020). Table 9 shows that the factor's correlation is less than 0.70; hence, discriminant validity is achieved.

Table 8: Kaiser-Meyer-Olkin measure of sampling adequacy

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.848
Bartlett's Test of Sphericity	Approx. Chi-Square	27278.786
	df	153
	Sig.	0.0001

Table 9: Factor correlation matrix

Factors	1	2	3	4	5
1	1.000	0.145	0.214	0.552	0.466
2	0.145	1.000	0.183	0.134	0.170
3	0.214	0.183	1.000	0.185	0.367
4	0.552	0.134	0.185	1.000	0.294
5	0.466	0.170	0.367	0.294	1.000

4.3. CFA

In this section, we will demonstrate a CFA using the five factors. The path diagram in Fig. 4 represents the measurement theory.

Fig. 4 shows that the factor loadings of each dimension and item of the teacher support scale ranged from 0.67 to 0.81, the factor loading of each dimension and item of the self-efficacy scale ranged between 0.61 and 0.76, the factor loading of each dimension and item of sense of school belonging scale ranged between 0.61 and 0.77, and the factor loading of each dimension and item of reading ability scale ranged between 0.66 and 0.74, these results indicate that factor loading standard of fit.

The convergent validity can be verified by computing each construct's Average Variance Extracted (AVE). The AVE must be higher than 0.50 to conclude that the observed variables achieved convergent validity. According to Hair et al. (2006), an AVE of 0.4 is also accepted. It indicates that the structure has sufficient convergence validity with all the $AVEs$ for each latent variable greater than 0.4; there is support for convergent validity for each latent variable, as shown in Table 10.

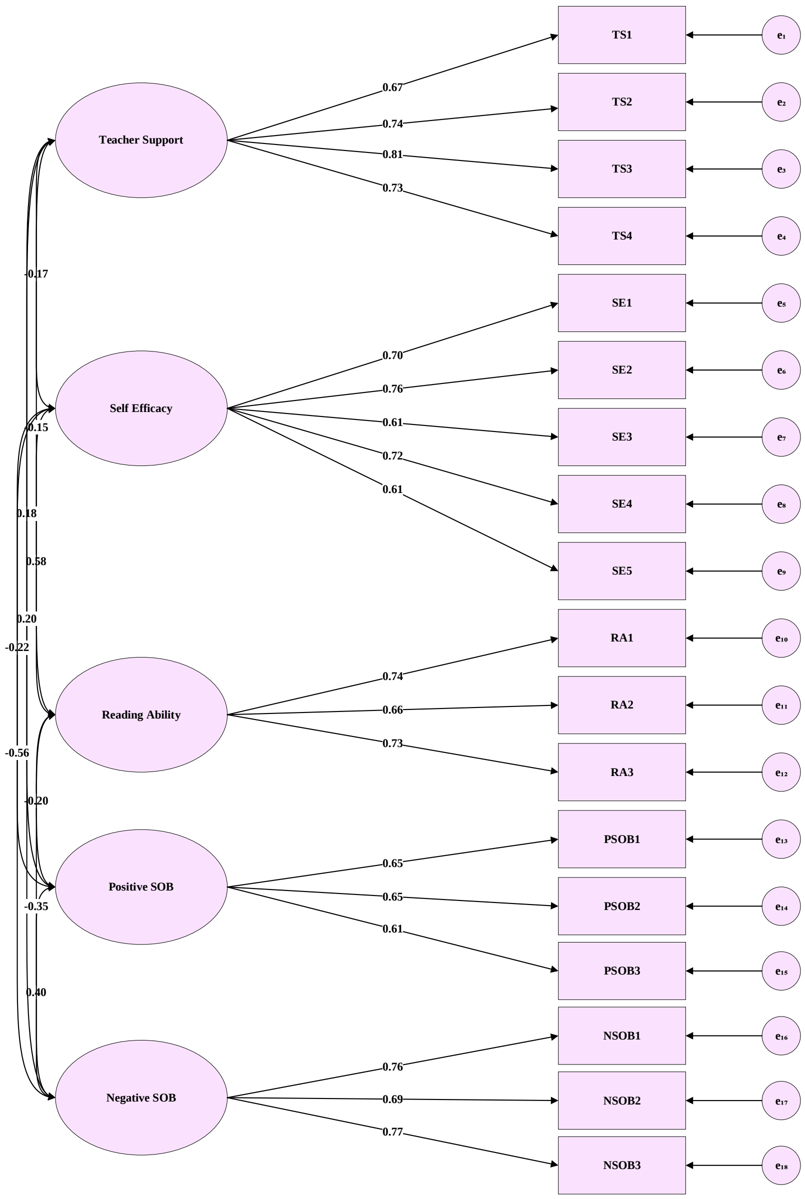

Fig. 4: CFA

Table 10: Results of the measurement model

Factors	*AVE*	Composite reliability
Self-efficacy	0.462	0.873
Reading ability	0.486	0.816
Sense of School belonging	0.62	0.875
Teacher support	0.55	0.871

We assessed the discriminant validity by examining the overlap in variance between constructs, analyzing the correlations between constructs, and squaring those correlations, as presented in Table 11. The resulting values, represented by the squared correlations in Table 11, should be smaller than the average variance extracted for each construct, as presented in Table 10. We found that all *AVE* values are higher than the shared variance between constructs, thereby providing evidence for the discriminant validity of our constructs in the model as presented in Table 10. Also, Table 10 shows that the composite reliability of all constructs exceeds 0.7, exceeding the recommended standard.

Table 11: Correlations between constructs

			Estimate	Square the correlations
Teacher support	<-->	Reading ability	-0.145	0.02
Teacher support	<-->	Self-efficacy	-0.154	0.023
Reading ability	<-->	Self-efficacy	0.545	0.297
Teacher support	<-->	Positive SOB	0.167	0.027
Teacher support	<-->	Negative SOB	0.076	0.005
Reading ability	<-->	Positive SOB	-0.196	0.038
Reading ability	<-->	Negative SOB	-0.142	0.02
Self-efficacy	<-->	Positive SOB	-0.226	0.051
Self-efficacy	<-->	Negative SOB	-0.201	0.04
Positive SOB	<-->	Negative SOB	0.133	0.017

Table 12 shows the selected output from testing a CFA model. It appears that the model fit is good, except $\chi^2/df = 7.03$, still in the unacceptable range. The fit between the theoretical model and observation data is considered acceptable.

Table 12: CFA goodness-of-fit statistics

Indices	Rule of thumb	
Overall model fit measures		$\chi^2 = 878.90829$ $df = 125$ $p = 0.000001$
	Absolute fit measures	
RMSEA	< 0.06	0.03
SRMR	< 0.06	0.0203
GFI	≥ 0.90	0.98
AGFI	≥ 0.90	0.97
	Incremental fit indices	
CFI	≥ 0.90 for acceptance	0.97
NFI	≥ 0.90 for acceptance	0.97
TLI	≥ 0.90 for acceptance	0.96
IFI	≥ 0.90 for acceptance	0.97
	Parsimony fit indices	
$\frac{\chi^2}{df}$	Between 2 and 5 are acceptable	7.03
PNFI	≥ 0.50	0.71

Modification index: In this context, a reduction in the χ^2/df ratio to indicate an improved fit. We identified the largest modification index to identify areas where adjustments may be needed in the model. In our analysis, the largest modification index was 89.65, which indicated that there may be a covariance of error terms between e_6 and e_9 as shown in Fig. 5. After implementing previous modifications, the χ^2/df ratio decreased from 7.03 to 4.81. To further improve the model fit, we identified the largest modification index once again, which was 38.74, and indicated a possible covariance of error terms between e_1 and e_3 as shown in Fig. 5. After previous modifications, the χ^2/df ratio decreased to 4.19. Therefore, the results suggest that the CFA model has an acceptable fit. Other fit indices, such as the Root Mean Square Error of Approximation (RMSEA), also showed improved covariances between error terms. The RMSEA decreased from 0.03 to 0.02, indicating a good fit. The CFA provides evidence that our indicators accurately measure their intended concept.

The result of the CFA with no common method factor included is shown in Table 13, and the result of the CFA with a common method factor included is in Table 14.

The comparison is conducted by checking the difference between the default models, which is 1 df, and the chi-square values are equal, as presented in Tables 13 and 14. Based on the results, the test for common method bias did not reach a significant level. The significance level of 1 df is 3.84 at a p-value of 0.05, and the difference between the models is below that threshold. Therefore, since the common method bias test is insignificant, the structural analysis should not include the common method latent factor.

Second-order CFA is two first-order constructs form the higher-order construct of a sense of belonging. A positive sense of belonging is assessed using three observed variables, while a negative sense of belonging is assessed using three observed variables. We conducted the higher-order analysis to determine if the model fits better than the first-order CFA model. Based on our findings, it can be concluded that the two models do not show any noteworthy differences. The first-order CFA model provides a reasonable explanation of the data with a χ^2/df value of 4.19, which only slightly increased to 4.22 in the second-order CFA model.

4.4. SEM

Fig. 6 presents the proposed model, which includes one dependent latent variable (reading ability) and three independent latent variables (self-efficacy, sense of belonging, and teacher support). SEM will be used to analyze the structural model, which focuses on examining the relationships between constructs. Two structural models were developed in this study. The first structural model is called path analysis. Path analysis examines the connections between constructs without including measurement model items. The goal is to test if self-efficacy and a Sense of belonging directly influence reading ability. In addition, Teacher support will be tested to check whether it indirectly and directly influences reading ability.

Table 13: Result of the CFA with no common method variable

Model	NPAR	CMIN	DF	P	$CMIN/DF$
Default model	48	515.75678	123	.00000	4.19314
Saturated model	171	.00000	0		
Independence model	18	44084.76307	153	.00000	288.13571

Table 14: Output of CFA with a common method variable included

Model	NPAR	CMIN	DF	P	$CMIN/DF$
Default model	49	515.75678	122	.00000	4.22751
Saturated model	171	.00000	0		
Independence model	18	44084.76307	153	.00000	288.13571

Hypothesized relationships:

$\boldsymbol{H_1}$**:** Students' perceived teacher support positively affects their reading ability.

$\boldsymbol{H_2}$**:** Students' sense of belonging mediates between perceived teacher support and reading ability.

$\boldsymbol{H_3}$**:** Students' self-efficacy mediates between perceived teacher support and reading ability.

The standardized regression analysis of the structural equation model is presented in Fig. 6. We found that teacher support has a statistically significant medium and positive effect ($\beta = 0.33$), $p = 0.001$ on the sense of belonging, and self-efficacy has a statistically significant strong positive effect ($\beta = 0.52$), $p = 0.001$ on reading ability. Besides this, teacher support has a negative, weak effect $\beta = -0.16$ on self-efficacy, which is statistically significant at $p = 0.001$, and sense of belonging has a weak negative effect $\beta = -0.19$ on reading ability, which is statistically significant at $p = 0.001$. Conversely, we found that the teacher support for reading ability was insignificant with $p = 0.868$.

The overall fit measure values are as follows: Measures of absolute fit: χ^2= 814.76394, χ^2/df = 6.466, RMSEA = 0.029. Incremental fit measures: CFI, IFI, NFI, and TLI were 0.984, 0.984, 0.981, and 0.980, respectively, within the acceptable range. Parsimonious fit measures: PNFI was 0.808. The above results show that the model fit is suitable for all the different model fit indices.

Fig. 6 shows the indirect relation between teacher support and reading ability through two mediators: self-efficacy and sense of belonging. We can conclude that teacher support significantly indirectly affects reading ability through the sense of belonging. Teacher support has a nonsignificant relationship with reading ability. This means that the influence of teacher support on reading ability is entirely mediated through the construct of a sense of belonging. The second mediator shown in Fig. 6 is self-efficacy. The indirect effect through the self-efficacy construct is significant.

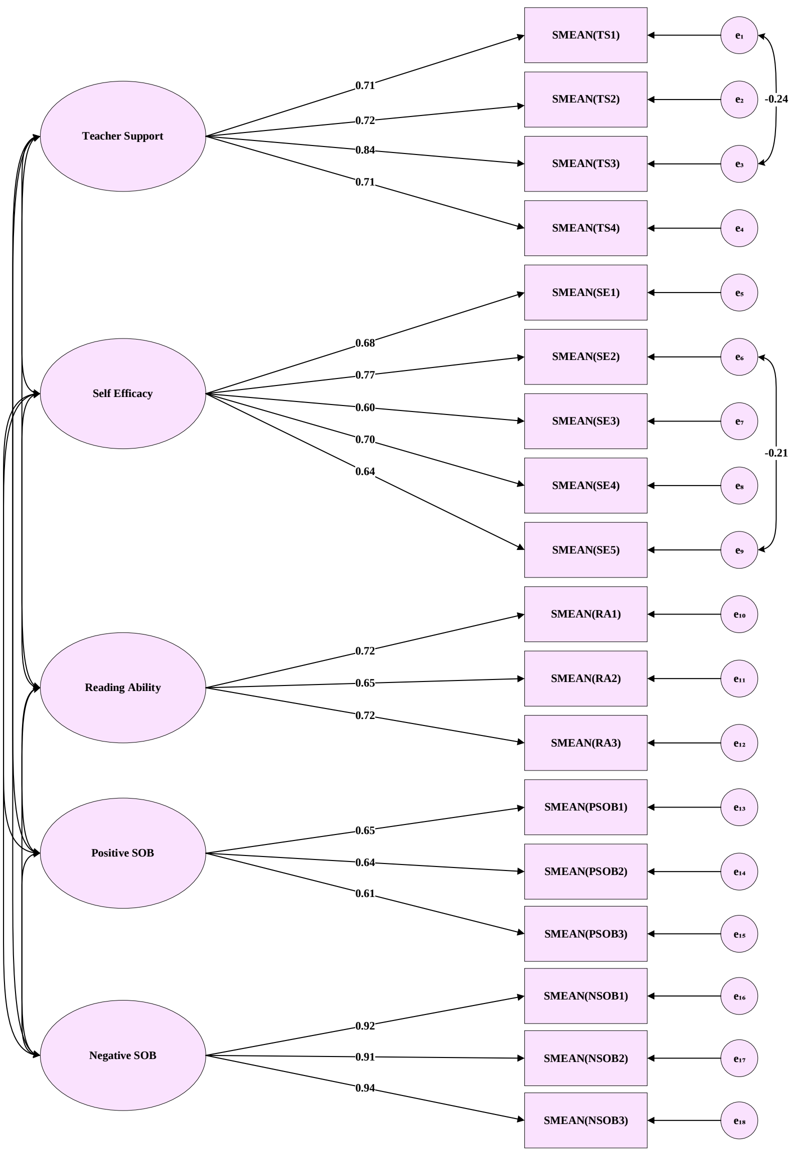

Fig. 5: Covariance of error terms

In the moderation model, gender acts as the moderator. Separate models were created for the "male" and "female" categories. The model fit statistics for the unconstrained model, with χ^2/df = 4.02, CFI = 0.98, and RMSEA = 0.02, show that the unconstrained model fits the data well. The results show that the exciting factor structure fits each group well; hence, configural invariance is achieved. Metric invariance is called measurement weights, and scalar invariance in AMOS that constrained the model is called measurement intercepts. From Table 15, we got insignificant results, with the difference in

NFI, IFI, and TLI being less than 0.05. We achieved measurement model invariance using configural, metric, and scalar invariance. Consequently, the relationship is not different across the groups.

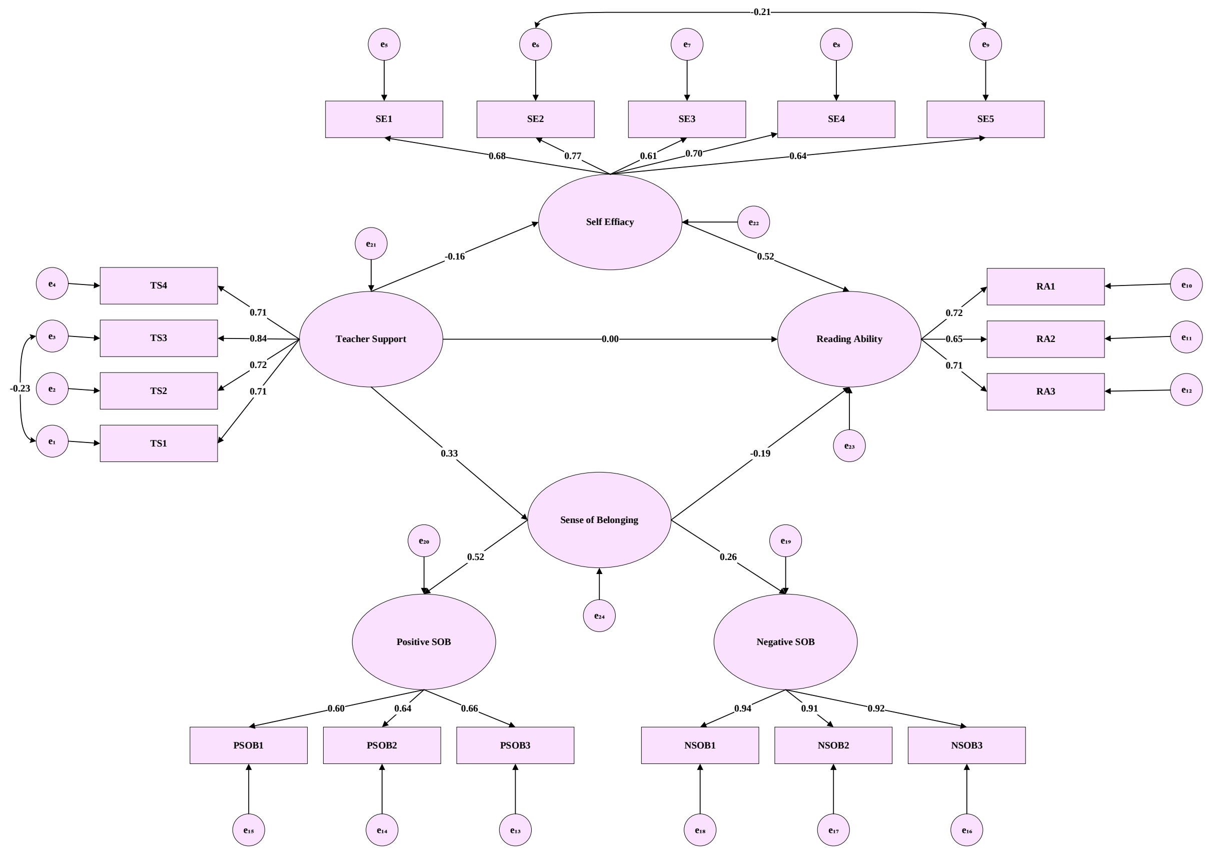

Fig. 6: Full structural model (standardized solution)

Table 15: Metric and scalar invariance

Model	ΔNFI	ΔIFI	ΔTLI
Measurement weights	0.00257	0.00259	0.00156
Measurement intercepts	0.02104	0.02116	0.01943

5. Conclusions

Using a research model based on the Theory of Social-Motivational Processes and Social Cognitive Theory, this study examined how students' perception of teacher support influences their reading ability. Additionally, the study explored the role of school belonging and self-efficacy as potential mediators in this relationship. The results indicated that the direct impact of 0.003 of students' perception of teacher support on their reading interest was insignificant. Similar findings in high school students in Thailand imply that students' perceptions of their teachers' support in the classroom do not necessarily lead to an interest in reading, for which the direct impact was 0.008. However, it was found that this perception indirectly increased their reading interest by enhancing their sense of school belonging and self-efficacy. In other words, students' sense of school belonging and self-efficacy fully mediated the relationship between their perception of teacher support and their reading interest. Chang and Bangsri (2020) further supported the previous results by applying SEM to Thai school students in PISA 2018. Even though teacher support does not directly enhance students' reading ability, it can boost their self-efficacy and sense of belonging to the school community, ultimately improving their reading skills. When students perceive the support and encouragement from their teachers, their self-assurance and belief in their abilities can be strengthened, which plays a crucial role in developing self-efficacy. This, in turn, enables students to embrace challenges and enhance their reading ability (Chang and Bangsri, 2020). This finding suggests that there is no evident connection between how Saudi high school students perceive teacher support in the classroom and their level of interest in reading. It is reinforced by the findings of the PISA 2018 survey, which revealed that 75% of students in Saudi Arabia, surpassing the OECD average of 74%, agreed or strongly agreed that their teachers demonstrate enjoyment in teaching. As noted previously, some descriptive results from the OECD show that students in Saudi Arabia and other countries and economies experienced higher reading scores when they perceived their teachers as more enthusiastic, especially when students said their teachers were interested in the subject (Markus, 2019). It indicated that although students' reading proficiency was low, they still felt their teacher supported them during class.

One of the important results noted in this study is that the relationships are the same between girls and boys, contrary to what was stated in the OECD report that girls are better than boys in reading achievement (Markus, 2019).

This research finding emphasizes the importance of teachers being mindful of their students' perceived self-efficacy and sense of belonging to the school. Teachers cannot rely solely on increasing students' liking for them and their courses, as this may not have a practical impact on their reading abilities. Upon analyzing the correlation between teacher support and students' reading achievement, a decline was observed in the frequency of teachers assisting students with their learning. It is, therefore, crucial to bring this matter to teachers' attention and emphasize its significance. Additionally, the research found that students' sense of belonging to the school was low, as indicated by their response to the question, "I feel like I belong at school." This suggests that students are dissatisfied with their sense of belonging to the school and the educational environment.

Consequently, efforts should be made, possibly by teachers or educators, to address this aspect and make students aware of its importance concerning their reading achievement. Therefore, initiatives to promote teacher support in schools should also focus on enhancing students' confidence and connection to their school. In my opinion, other questions may be more relevant to students' sense of belonging and their perception of teacher support. Educators, policymakers, and stakeholders in the Saudi Arabian education system could further explore this.

6. Future work

While direct teacher support may not directly impact improving students' reading ability, it positively influences their sense of belonging and self-efficacy. As a result, students still require the support and encouragement of teachers to cultivate a sense of belonging and self-efficacy, which can ultimately enhance their reading skills. This conclusion was derived from the data analysis conducted in this study and can serve as a blueprint for future research.

Compliance with ethical standards

Ethical considerations

This study utilized anonymized, publicly available data from PISA 2018, which complies with ethical standards. No direct data collection from participants was involved, and confidentiality was maintained throughout the analysis.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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