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Selection Criteria of Appropriate Methods Between Covariance-Based, Partial Least Squares, and Generalized Structured Component Analysis in Structural Modeling

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ABSTRACT

This study employs covariance-based (CB), partial least squares (PLS), and Generalized Structured Component Analysis (GSCA) to model the relationships between Participatory, Transparent, and Accountable School Management (PS), Teacher Competence and Performance (KG), Learning Quality and Relevance (MR), and Learning Achievement (CP) using National Assessment (AN) data from 833 senior secondary schools (SMA) in Indonesia. CP is measured at the school level in terms of numeracy, literacy, and character, while MR is positioned as a mediating variable linking PS and KG to CP. Because the indicator data deviate from multivariate normality, the CB model is estimated with a robust MLR estimator, while PLS and GSCA are treated as component-based alternatives. In all three SEM frameworks, PS exhibits a strong and significant effect on MR, KG shows a positive but relatively small effect on MR, and MR demonstrates a moderate and significant effect on CP. The R^2 for MR is high, whereas the R^2 for CP is moderate, indicating that factors outside the model also influence learning outcomes. Substantively, the findings underscore the strategic role of school management and classroom learning quality, while methodologically, they offer empirical insights into the application of CB, PLS, and GSCA to non-normally distributed data.

1. INTRODUCTION

Multivariate data generally consists of several interrelated observed variables, which in some cases can be interpreted as indicators of one or more latent constructs in a structural model. Various Structural Equation Modeling (SEM) techniques are covariance-based (CB) and variance-based methods, including Partial Least Squares (PLS) and Generalized Structured Component Analysis (GSCA) [1]. CB examines and validates theories by assessing the degree to which suggested theoretical models can generate the covariance matrix of observed sample data [2]. This method can assess measurement errors from its indicators, leading to more precise parameter estimates [3]. Nonetheless, CB necessitates multivariate normality and independence among data, rendering it inappropriate for small sample sizes [4].

In contrast to CB, PLS was conceived as a causal-predictive methodology that emphasizes elucidating variance in dependent variables, rendering it more appropriate for investigating links between variables rather than solely for testing theories [5]. In PLS, latent variables are termed "components," which are linear combinations of observable indicators, with each indicator weighted based on its contribution to elucidating the component [6]. The primary benefit of PLS is its capacity to produce distinct scores for each observation once the indicator weights are established. Moreover, PLS is renowned for its suitability for small sample sizes [7]. PLS is inapplicable for non-recursive interactions among components and lacks a comprehensive goodness-of-fit (GoF) metric for evaluating model adequacy [8].

In the advancement of variance-based methodologies, GSCA was established to address increasingly intricate interactions among latent variables. GSCA was initially introduced by Hwang et al. [9] by integrating the advantages of PLS with enhanced estimating methodologies, enabling it to manage diverse data types and intricate interactions. GSCA has more adaptable latent components to accommodate data that fails to satisfy linearity or normalcy criteria. GSCA has demonstrated efficacy in discerning correlations among latent variables across diverse sample sizes, including scenarios with constrained samples and a restricted number of indicators [10]. Prior simulation experiments have additionally shown that GSCA effectively recovers structural characteristics across a range of sample sizes, from small to large [11]. This method does not necessitate stringent distributional assumptions and yields a GoF index [12].

Recently, the utilization of CB, PLS, and GSCA methodologies has gained significant traction across diverse multidisciplinary research. Vukovic [13] employed PLS and CB models to forecast stock investment intentions grounded in the Theory of Planned Behaviour (TPB). Rigdon et al. [14] analyzed CB and PLS methodologies in the context of marketing data and offered pragmatic guidance for selecting a suitable approach. Sarstedt et al. [15] employed PLS and CB models to investigate bias in marketing data. Civilek [16] demonstrated that causal Bayesian (CB) analysis excels in examining causal links with several variables. Cho and Choi [17] utilized GSCA and PLS on consumer behavior survey data with limited sample sizes. Dash and Paul [18] examined CB, PLS, and PLS in relation to technological and social change data. Shen et al. [19] examined three SEM methodologies in psychological data and demonstrated that GSCA effectively manages interaction models across components. Susetyo and Fitrianto [20] examined the quality of accrediting processes and National Examination (UN) outcomes utilizing a multilevel GSCA methodology.

Participatory, Transparent, and Accountable School Management (PS) in this study is framed within the context of School-Based Management (SBM), which emphasizes transparent management, community participation, and active, creative, effective, and pleasant learning. The execution of SBM, guided by the principles of transparency, accountability, and significant stakeholder engagement, enhances the school's organizational climate, bolsters public trust, and facilitates the enhancement of educational quality, consistent with the tenets of good governance in education [21].

Teacher Competence and Performance (KG) is widely regarded as one of the main determinants of learning quality. Research shows that teachers' professional competence mastery of subject matter, pedagogical knowledge, and ability to manage learning is closely related to the quality of teaching and student learning outcomes [22]. Teachers with high levels of competency are better able to design meaningful learning, provide clear explanations, use formative assessment effectively, and adapt learning to student needs, thereby directly improving the Learning Quality and Relevance (MR) experienced by students in the classroom.

The correlation between MR and Learning Outcomes (CP) can be elucidated using the process–product model framework in educational research. Within this approach, variables at the school and educator levels do not directly influence student accomplishment but rather exert their effects through the caliber of the classroom learning experience. Learning quality is typically characterized by a set of visible instructional traits that are both theoretically and empirically linked to enhanced learning outcomes [23]. Global research indicates that students' evaluations of instructional quality in mathematics significantly influence their mathematical literacy achievement, as evidenced by the 2012 PISA survey conducted in Turkey [24]. A systematic review by Christ et al. [25] revealed that student learning processes frequently mediate the relationship between teaching quality and academic achievement, thereby affirming the pivotal role of learning quality as a conduit between school/teacher conditions and student learning outcomes.

This study defines CP as school-level learning outcomes encompassing numeracy competence, reading competence, and character, whereas MR is conceptualized as the principal mediating process that conveys the impact of PS and KG on these outcomes. The proposed model categorizes PS and KG as exogenous constructs indicative of school management conditions and teacher-related characteristics, whereas MR and CP are classified as endogenous constructs that characterize the classroom learning process and aggregate learning results at the school level.

PLS and GSCA are frequently emphasized in the literature for their capacity to manage small sample sizes. Nonetheless, this benefit was not the primary impetus for this investigation, as the sample size employed (N = 833) was sufficient for CB analysis. The choice of PLS and GSCA in this study is primarily influenced by the observation that empirical data exhibit substantial deviations from the assumption of multivariate normality and that, statistically, PLS and GSCA model constructs are component-based, rendering both methodologies pertinent to be evaluated alongside CB in this context. Utilizing the three SEM frameworks on the same empirical data set allows for an evaluation of their efficacy and the methodological ramifications under uniform empirical settings. PS, KG, MR, and CP fundamentally denote identical theoretical constructs across all three methodologies. In CB, these constructs are represented as common factors, while in PLS and GSCA, they are operationalized as composites, illustrating the component-based characteristics of these two methodologies. Consequently, each method exhibits distinct advantages and drawbacks based on the employed evaluation criteria.

Based on the previous description, this study aims to apply CB, PLS, and GSCA to analyze education quality using National Assessment (AN) data for senior high school level in Indonesia and to discuss the substantive and methodological insights that emerge from these applications. Theoretically, CB, PLS, and GSCA can all be used to analyze structural models in empirical data, but they differ in their underlying assumptions, objectives, and evaluation criteria.

2. MATERIAL AND METHOD

2.1 Dataset

This study utilizes data from the AN, encompassing instruments from the Minimum Competency Assessment (AKM), Character Survey, and Learning Environment Survey, as published in the School Education Report by the Ministry of Education of Indonesia [26]. This study's sample comprises 833 senior high schools in Indonesia for the year 2023. Sampling was executed by stratified random sampling to guarantee equitable representation according to strata types, namely each province, with schools randomly picked within each stratum. The dataset comprised 17 indicators measured on a range of 0-100, resulting in four latent variables: two endogenous and two exogenous latent variables (refer to Table 1).

2.2 CB

The CB model comprises two primary components: confirmatory factor analysis (CFA) and structural models. CFA delineates the association between latent variables and their corresponding measurement indicators [27], whereas structural models elucidate the interrelations among latent variables [28]. The measuring model in CB only employs reflective models [29], as delineated in Eq. (1).

$$y = \Lambda\eta + \varepsilon;\ x = \Lambda\xi + \delta \quad (1)$$

where, y is an indicator for the endogenous latent variable η, x is an indicator for the exogenous latent variable ξ, Λ is the loading matrix, ε and δ are measurement errors, $\varepsilon \sim N(0, \Theta)$ and $\delta \sim N(0, \Theta)$. Meanwhile, the structural model as presented in Eq. (2):

$$\eta = B\eta + \Gamma\xi + \zeta \tag{2}$$

where, η, ξ, and ζ are endogenous latent variables, exogenous latent variables, and structural errors, $\zeta \sim N(0, \Psi)$.

The maximum likelihood estimation (MLE) method is used to estimate the CB model parameters [30]. Before estimating the MLE parameters, model identification and model specification are carried out first. This is followed by parameter estimation, which aims to form a model covariance matrix that matches the sample data. The model covariance matrix $\Sigma(\theta)$ is presented in formula (3):

$$\begin{bmatrix} \Lambda_y\left[(I-B)^{-1}(\Gamma\Phi\Gamma' + \Psi)(I-B)^{-1'}\right]\Lambda_y' + \Theta_\varepsilon & \Lambda_y(I-B)^{-1}\Gamma\Phi\Lambda_x' \\ \Lambda_x\Phi\Gamma(I-B)^{-1}\ \ \Lambda_y' & \Lambda_x\Phi\Lambda_x' + \Theta_\delta \end{bmatrix} \tag{3}$$

where, (*I*-*B*) is a nonsingular matrix and θ represents the estimated parameter. The parameter estimation process is carried out by minimising the function $F(S, \Sigma(\theta))$. This objective function can be expressed as Eq. (4):

$$\mathrm{F}_{ML} = ln|\Sigma| + tr[(S)(\Sigma^{-1})] - ln|\mathrm{S}| - P \tag{4}$$

$|\mathrm{S}|$ and $|\Sigma|$ are the determinants of the sample covariance matrix and model covariance matrix, respectively, while P is the number of indicator variables. After parameter estimation, a model fit test is carried out as shown in Table 2 [31].

Table 1. List of indicators and latent variables

Construct	Indicators	Conceptual Definition
PS	PS1	Level of participation of parents and students in school management
	PS2	School programs and policies on bullying
	PS3	Programs and policies regarding the mitigation and prevention of intolerance in schools
	PS4	Implementation of programs that support gender equality
	PS5	The school's vision and mission
KG	KG1	Proportion of certified educators
	KG2	Minimum educator proportion: Bachelor's degree
MR	MR1	Classroom environment that supports learning according to teachers
	MR2	Interactive activities according to teachers
	MR3	Teachers' attention and care according to teachers
	MR4	An atmosphere that encourages students to have and express their personal opinions on various socio-cultural issues based on the teacher's views
	MR5	Level of reflection and improvement of learning by special teachers' assessment of reflection on teaching practices
	MR6	Teachers' adaptation practices in response to student feedback and responses to learning needs based on teachers' perspectives
	MR7	Communication of teachers' evaluations of students' work and behaviour to motivate students to continue improving their abilities based on the teachers' perspectives
CP	CP1	Numeracy competence
	CP2	Literacy competence
	CP3	Character index

Table 2. Model fit for covariance-based

Model Fit Test	Name	Level of Acceptance
Overall model fit	Goodness of Fit Index (GFI)	GFI > 0.90 is a good fit.
	Standardized Root Mean Square Residual (SRMR)	SRMR < 0.05 is a good fit.
	Comparative Fit Index (CFI)	RMSEA < 0.08, range 0.05 to 1.00 acceptable. CFI > 0.90 is a good fit.
Measurement model fit	Average Variance Extracted (AVE)	AVE > 0.50, the validity is achieved.
	Composite Reliability (CR)	CR ≥ 0.70 is good reliability.
Structural model fit	Coefficient of Determination (R^2)	The proportion of endogenous variable diversity explained by the model (the better the structural fit).

2.3 PLS

Unlike CB, PLS uses three main components: outer model, inner model, and weight relation. The outer model describes the relationship between latent variables and their indicators, which can be reflective or formative. In this study, we used exogenous latent variables with reflective indicators and a structural model, as presented in Eq. (5) and Eq. (6):

$$x = \Lambda\xi + \delta \tag{5}$$

$$\eta = \beta\eta + \Gamma\xi + \zeta \tag{6}$$

where, x is the indicator; η and ξ are endogenous and exogenous latent variables; ζ is the residual; β is the path coefficient between endogenous latent variables, and Γ is the effect of exogenous on endogenous latent variables.

In the PLS, the outer and inner models provide specifications followed by weight estimation. Latent scores are estimated as a linear combination of indicator variables, as presented in Eq. (7):

$$\hat{\xi} = \widetilde{w}x \tag{7}$$

where, $\widetilde{w}$ is the weight vector used to form the latent component score $\hat{\xi}$ through a linear combination of indicators x [32].

The least squares method is used to estimate parameters through an iterative procedure [33]. Parameter estimation consists of three main things, namely

(i) Weight estimation;
(ii) Path coefficient estimation;
(iii) Loading and weight estimation.

Measurement model evaluation uses AVE and CR, as done by CB and R^2, Q^2 for structural.

2.4 GSCA

GSCA consists of three integrated submodels, namely the measurement model, the structural model, and the weighted relation model, each presented in Eqs. (8)-(10) [34]:

$$z = C'\gamma + \varepsilon \tag{8}$$

$$\gamma = B'\gamma + \zeta \tag{9}$$

$$\gamma = W'z \tag{10}$$

where, z is the indicator, γ is the latent component, C is the loading that connects the latent variable with the indicator, ε is the residual of the indicator, B is the path coefficient, ζ is the residual of γ, and W is the component weight. Specifically, the three submodels are integrated into a single model, as follows:

$$V'z = A'W'z + e \tag{11}$$

in which $V = \begin{bmatrix} I \\ W' \end{bmatrix}, A = \begin{bmatrix} C' \\ B' \end{bmatrix}, e = \begin{bmatrix} \varepsilon \\ \zeta \end{bmatrix}$, $V'z$ consists of all indicators and latent variables, A is a matrix that includes all loadings and path coefficients, and e is a residual [35]. As an illustration, a recursive GSCA structural equation model is provided in Figure 1.

The Alternating Least Squares (ALS) method is used to estimate GSCA parameters through an iterative process that optimises model parameters alternately between the latent variable weight matrix (V), indicator loading matrix (W), and path coefficient matrix (A) [36]. The estimation process aims to minimise the smallest square value of all residuals. This is equivalent to minimising the least square criterion, namely $\phi = SS(V'z - A'W'z)$. Schlittgen [37] explained that the ALS algorithm used in GSCA consists of two steps. In the first step, A is estimated with V and W fixed, while in the second step, V and W are estimated with A fixed.

The evaluation of the GSCA model includes the measurement model, structural model, and overall goodness of fit. The evaluation of the measurement model in GSCA is similar to that conducted in CB and PLS. Similarly, the assessment of the structural model uses R-squared to measure using the FIT and Adjusted FIT tests as follows [31]:

$$FIT = 1 - \left[\frac{trace\ (V'z - A'W'z)'(V'z - A'W'z)}{trace((V'z)'(V'z))}\right]$$

$$AFIT = 1 - (1 - FIT)\frac{d_0}{d_1}$$

where, $d_0 = N * J$, $d_1 = N * J - k$, d_0 is the degrees of freedom of model 0 (W = 0 and A = 0), d_1 is the degrees of freedom of the tested model, and k is the number of parameters. The FIT value ranges from 0 to 1 and can be interpreted as the data diversity the model can explain. The model with the highest AFIT value is considered the best model.

2.5 The procedure of data analysis

The data analysis procedure in this study consists of several stages, beginning with data pre-processing, then data exploration, and structural model formation. Next, modelling was carried out using CB, PLS, and GSCA models and evaluation through measurement model analysis, structural model analysis, and overall goodness of fit analysis. This stage aims to identify the relationship between variables and evaluate the model's suitability with the existing data. The research flowchart is shown in Figure 2.

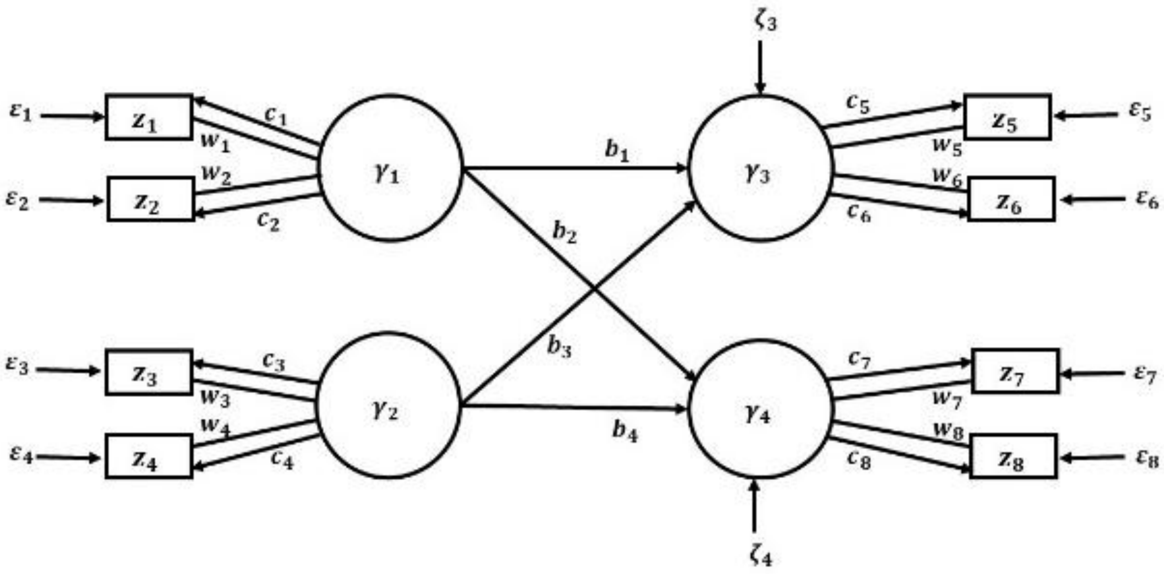


Figure 1. Recursive GSCA path diagram with reflective indicators

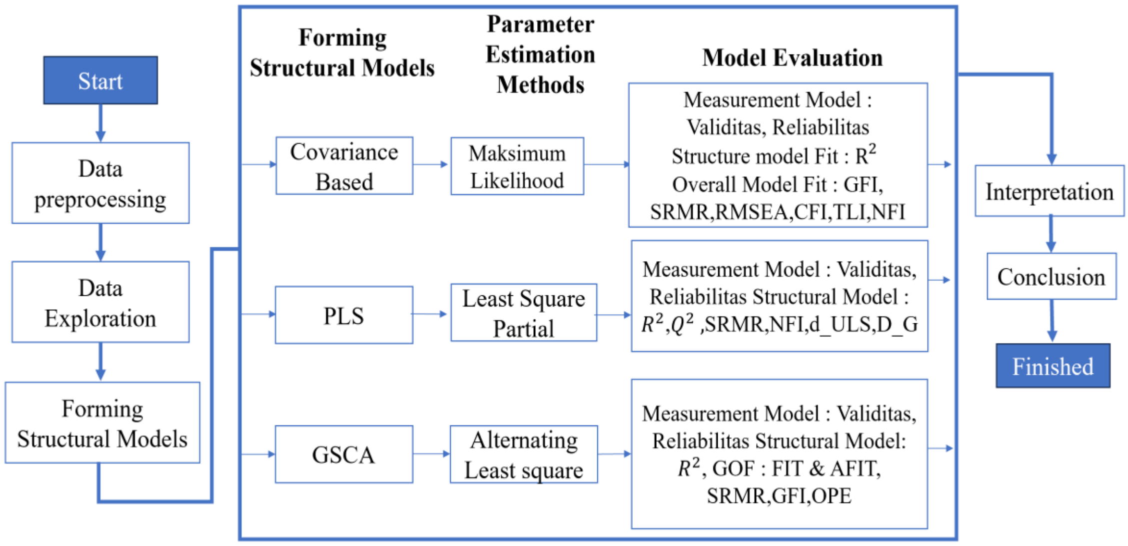


Figure 2. The research flowchart

3. RESULTS AND DISCUSSIONS

This section presents data analysis, focusing on measurement models, structural models, and performance evaluations of CB, PLS, and GSCA models. Key findings and their implications are discussed.

3.1 Result

Table 3 describes the characteristics of schools participating in the AN, which are used to illustrate the diversity of school environments in the sample. The results of the descriptive analysis show significant variation. Most of the respondent schools are located in Western Indonesia (61.35%), followed by Central Indonesia (30.49%), while Eastern Indonesia has a very small representation (8.16%). Regarding curriculum implementation, 74.67% of schools have adopted the Merdeka Curriculum, while 25.33% still use the 2013 Curriculum. In terms of institutional status, public schools accounted for 55.22%, while private schools accounted for 44.78%. In addition, only 2.88% of schools were located in specific geographical areas as stipulated by the Ministry of Education, Culture, Research, and Technology, Number 160/P/2021, while the remaining 97.12% were outside this classification. In terms of administration, there are far more schools in districts than in cities, with a percentage of 77.31% compared to 22.69%. Currently, most schools are located in rural areas (54.38%), while the rest are in urban areas (45.62%).

Table 4 presents descriptive statistics for all research indicators. In general, the participatory, transparent, and accountable school management (PS1–PS5) shows average scores in the moderate to high range. PS1 and PS3 exhibit the highest averages and moderate standard deviations, suggesting that the majority of schools have engaged the school community in management and possess relatively effective strategies for managing intolerance, but with some discrepancies among schools. Conversely, PS2, PS4, and particularly PS5 have lower averages and more variability, indicating that anti-bullying initiatives, gender equity, and the internalization of the school's vision and mission in education have not been uniformly executed across all institutions.

In the KG framework, the KG1 indicator reveals a low mean percentage of certified educators accompanied by a significant standard deviation. This signifies a pronounced disparity among schools: certain institutions possess nearly no certified teachers, whereas others have a substantial abundance. In contrast, KG2 exhibits a notably high average with minimal variance, signifying that most schools possess a substantial proportion of teachers holding at least a bachelor's degree, while only a limited number of schools remain deficient in academic qualifications.

The quality and relevance of learning indicators (MR1–MR7) vary from moderate to high. MR1 and MR2 indicate that the learning environment at numerous schools is generally favorable; nonetheless, the disparity in scores implies that certain institutions must enhance the uniformity of interactive learning methodologies. MR3 and MR7 exhibit elevated averages accompanied by relatively low standard deviations, indicating that educational approaches tailored to student need and the delivery of excellent feedback have been regularly used across numerous institutions. Concurrently, MR4–MR6 have moderate averages with a wider dispersion, signifying that these elements are not yet uniformly allocated among all schools.

Table 3. School profile of AN participant

Category	Sub-Category	Total of School	Percentage
Region	Western	511	61.35
	Central	254	30.49
	Eastern	68	8.16
curriculum	Merdeka	622	74.67
	2013	211	25.33
School status	Public	460	55.22
	Private	373	44.78
Geographically Disadvantaged Areas	Yes	24	97.12
	No	809	2.88
Region Type	Regency	644	77.31
	City	189	22.69
School area	Rural	453	54.38
	Urban	380	45.62

Table 4. Descriptive statistics of the research variables

Indicators	Mean	SD	Min	Max	Skewness	Kurtosis
PS1	75.12	5.53	50.27	95.86	0.06	1.21
PS2	65.00	8.45	41.86	97.71	0.58	0.84
PS3	76.53	9.37	30.86	93.77	-0.75	1.09
PS4	65.14	6.27	43.83	96.04	0.76	1.83
PS5	48.89	8.06	25.59	84.16	1.03	1.72
KG1	28.38	22.48	0.00	100.00	0.40	-0.84
KG2	97.37	6.51	33.33	100.00	-4.04	22.18
MR1	68.25	7.18	46.31	96.01	0.22	0.98
MR2	66.46	6.70	39.91	100.00	0.08	1.53
MR3	82.12	5.16	63.09	99.32	-0.33	0.84
MR4	57.71	5.74	32.37	94.09	0.77	3.38
MR5	61.90	5.19	36.20	91.66	0.68	3.41
MR6	59.23	6.52	34.40	95.96	0.44	2.16
MR7	87.62	4.48	67.30	100.00	-0.39	0.92
CP1	55.58	7.13	32.93	83.93	0.26	0.83
CP2	64.90	10.61	25.31	91.47	-0.33	0.23
CP3	56.08	5.08	34.41	83.26	0.72	2.67

In learning outcomes, CP1 scores exhibited the lowest average with moderate variability, suggesting that numeracy proficiency remains comparatively deficient and necessitates targeted enhancement in certain institutions. CP2 exhibits the greatest average; nonetheless, the substantial standard deviation indicates a disparity in literacy proficiency among schools. CP3 exhibits a moderate mean with minimal variation, indicating that character success is more uniformly spread across schools, despite the presence of certain institutions with poor scores. Overall, the skewness and kurtosis values of the majority of indicators fall within a moderate range and exhibit minimal deviation from a normal distribution, with the exception of KG2 and PS5, which demonstrate elevated skewness and kurtosis, indicating a concentration of exceptionally high scores (KG2) and lower scores (PS5). Figure 3 illustrates that the distribution of indicator data does not completely adhere to the assumption of normality. Nonetheless, Mardia's test indicates that the variables do not meet the criteria for multivariate normality (refer to Figure 4).

The maximum likelihood (ML) estimator in CB is contingent upon the adherence to the multivariate normality assumption. Contravention of this assumption leads to erroneous parameter estimates, standard errors, and test statistics. This study uses the robust MLR (ML with robust standard errors), utilizing the lavaan package in R. Prior to doing measurement model analysis, the model identification method yielded a degree of freedom of 146 > 0, signifying that the model is overidentified. The findings of the CB analysis indicate that, overall, all factor loadings are significant, with the exception of KG2 (0.33), which fails to meet the criterion (> 0.50 in scientific study). Consequently, this indicator was eliminated from the KG build. The CB model was subsequently re-specified with KG represented by a singular indicator, specifically KG1 (refer to Table 5).

The PLS model was calculated utilizing the plspm package in R and SmartPLS software [38]. All indicator loadings were statistically significant at the 95% confidence level, varying from 0.654 to 0.927. This signifies that each indicator sufficiently represents the hidden construct being assessed. The AVE and composite reliability values for all constructs fell within an acceptable range, so affirming convergent validity and construct reliability.

The GSCA model was estimated utilizing GSCA Pro software [36] and the gesca package in R. During the estimate process using gesca, the iterative approach achieved convergence after four iterations, as the variation in the objective function fell below 1×10^{-4}. The GSCA model estimated 21 parameters from 833 observations, indicating an appropriate ratio of samples to parameters to ensure the stability and reproducibility of the estimation.

Furthermore, 100 bootstrap samples were employed to empirically derive standard errors and confidence ranges, so assessing path coefficients and indicator loadings was not solely based on point estimates but also by accounting for estimation uncertainty. The GSCA results indicate that the majority of constructs exhibit convergent validity and sufficient reliability, with significant loading values at a 95% confidence interval. Table 5 additionally displays weight estimates for the observed variables inside the empirical model. The findings indicate that all weight values for each latent variable are statistically significant. This signifies that all seen factors contribute equally to the formation of latent variables.

Furthermore, discriminant validity, as per the Fornell-Larcker criterion, indicates that all latent variables exhibit strong discriminant validity across the three structural models, with the exception of the correlation between PS and MR in the CB model (refer to Table 6). The latent correlation attained 0.91, surpassing the square root of the AVE for both constructs, hence failing to satisfy the Fornell–Larcker criterion for this pair. This suggests that the two hidden variables are statistically challenging to differentiate. The interpretation of the distinct contributions of PS and MR in the structural model requires careful consideration, and further study may explore more nuanced measurement requirements or incorporate new data sources.

In the CB, PLS, and GSCA models, the association between Participatory, Transparent, and Accountable School Management (PS) and the quality and relevance of learning (MR) has a robust and significant impact, with path coefficients of 0.89, 0.83, and 0.84 (Table 7). These findings align with the research that underscores the significance of participative, transparent, and responsible school management in enhancing the quality and relevance of education. The path coefficients of KG on MR are modest (about 0.12–0.13) yet remain significant across all three methodologies. This suggests that, upon accounting for the variance elucidated by PS, the distinct impact of KG on the quality and relevance of learning (MR) is constrained. A potential explanation is that the KG indicators employed in this study capture just a subset of the dimensions of teacher competence and performance pertinent to learning practices, hence failing to properly represent the substantive impact of KG on MR within the model. Moreover, MR exerts a substantial influence on CP, with path coefficients of 0.44 for CB, 0.49 for PLS, and 0.48 for GSCA. The data suggest that an elevation in MR may positively influence CP.

The CB model estimates a covariance of 0.18 between the latent variables PS and KG. The positive covariance suggests that schools characterized by participatory, transparent, and accountable management generally exhibit elevated levels of teacher competence and performance. This covariance should be seen as a statistical connection devoid of causal direction, rather than as proof of a causal relationship between PS and KG.

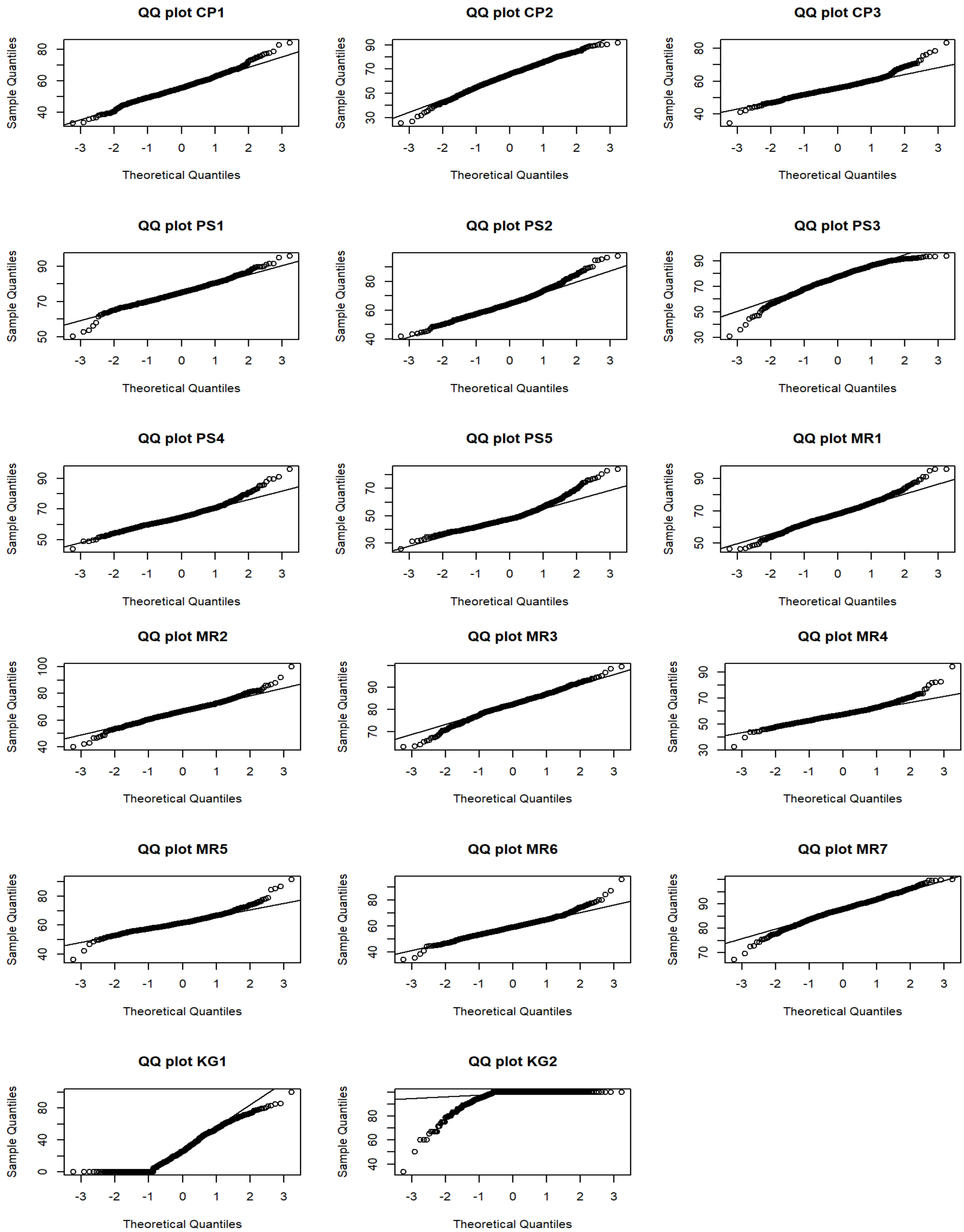


Figure 3. Visualisation of research indicator data distribution through a quantile-quantile (QQ)-plot

Table 5. Loading factor, convergent validity, and reliability for the construct

Contruct	CB			PLS			GSCA			
	Loading (p-value)	AVE	CR	Loading (95% CI)	AVE	CR	Loading (95% CI)	Weight (95% CI)	AVE	CR
Participatory, Transparent, and Accountable School Management		0.64	0.90		0.70	0.92			0.70	0.92
PS1	0.62***			0.73 (0.70-0.79)			0.74 (0.69-0.77)	0.20 (0.18-0.21)		
PS2	0.88***			0.91 (0.89-0.92)			0.91 (0.89-0.92)	0.24 (0.22-0.26)		
PS3	0.63***			0.74 (0.72-0.79)			0.74 (0.71-0.77)	0.19 (0.17-0.20)		
PS4	0.86***			0.85 (0.84-0.87)			0.85 (0.83-0.87)	0.31 (0.29-0.33)		
PS5	0.94***			0.94 (0.93-0.95)			0.94 (0.93-0.95)	0.25 (0.23-0.37)		
Teacher Competence and Performance		1.00	1.00		0.59	0.74			0.60	0.75
KG1	1.00***			0.87 (0.77-0.95)			0.78 (0.76-0.80)	0.66 (0.64-0.68)		
KG2				0.66 (0.48-0.78)			0.77 (0.74-0.78)	0.64 (0.62-0.66)		
Quality and Relevance of Learning		0.72	0.95		0.76	0.96			0.76	0.96
MR1	0.88***			0.90 (0.87-0.91)			0.90 (0.88-0.91)	0.17 (0.15-0.18)		
MR2	0.82***			0.85 (0.80-0.86)			0.85 (0.82-0.88)	0.15 (0.13-0.17)		
MR3	0.75***			0.79 (0.74-0.80)			0.79 (0.76-0.82)	0.16 (0.15-0.17)		
MR4	0.90***			0.91 (0.88-0.93)			0.91 (0.90-0.93)	0.17 (0.16-0.19)		
MR5	0.84***			0.85 (0.84-0.89)			0.86 (0.83-0.88)	0.19 (0.17-0.21)		
MR6	0.90***			0.91 (0.89-0.92)			0.91 (0.90-0.92)	0.17 (0.15-0.19)		
MR7	0.84***			0.87 (0.85-0.89)			0.87 (0.85-0.89)	0.14 (0.13-0.16)		
Learning Outcomes		0.73	0.89		0.80	0.92			0.80	0.92
CP1	0.94***			0.92 (0.89-0.94)			0.93 (0.91-0.94)	0.39 (0.35-0.43)		
CP2	0.96***			0.93 (0.91-0.94)			0.94 (0.93-0.95)	0.36 (0.32-0.38)		
CP3	0.63***			0.83 (0.79-0.86)			0.81 (0.78-0.85)	0.37 (0.36-0.39)		

Table 6. Discriminant validity according to the Fornell-Larcker criterion

Contruct	CB				PLS				GSCA			
	CP	PS	KG	MR	CP	PS	KG	MR	CP	PS	KG	MR
CP	0.86				0.89				0.89			
PS	0.41	0.80			0.44	0.84			0.43	0.82		
KG	0.12	0.18	1.00		0.36	0.18	0.77		0.34	0.18	0.77	
MR	0.44	0.91	0.27	0.83	0.49	0.86	0.28	0.87	0.48	0.86	0.28	0.87

Table 7. Relationship among latent variables: CB, PLS, GSCA

Hypothesis	CB		PLS		GSCA	
	Estimate (p-value)	Std. Error	Estimate (95% CI)	Std. Error	Estimate (95% CI)	Std. Error
MR ← PS	0.89 (0.00)	0.09	0.83 (0.82–0.85)	0.01	0.84 (0.81–0.86)	0.01
MR ← KG	0.12 (0.01)	0.01	0.13 (0.10–0.17)	0.02	0.12 (0.08–0.17)	0.02
CP ← MR	0.44 (0.00)	0.04	0.49 (0.43–0.54)	0.03	0.48 (0.42–0.54)	0.03

Table 8. Model fit indices: CB, PLS, and GSCA

Criterion	CB	PLS	GSCA
SRMR	0.08	0.08	0.06
Robust RMSEA	0.12		
Robust CFI	0.90		
Robust TLI	0.88		
NFI	0.86	0.83	
d_ULS		0.88	
D_G		0.44	
GFI	0.81		0.98
FIT			0.64
AFIT			0.64

Table 9. Evaluation of structural models

	CB		PLS		GSCA	
	MR	CP	MR	CP	MR	CP
R^2	0.84	0.20	0.75	0.24	0.77	0.23
Q^2			0.56	0.18		

Path analysis was undertaken using a structural model that first needs to be evaluated for model feasibility (refer to Table 8). In CB, different indices are provided to measure model fit in greater detail, like SRMR (0.08) at a general limit of 0.08; thus, it can still be categorized as relatively acceptable covariance residuals. However, the robust RMSEA score (0.12) is above the threshold, indicating a considerable model mismatch with the data. Comparative fit indices indicate a diversified pattern: a robust CFI of 0.90 meets the minimum requirement, whereas robust TLI (0.88) and NFI (0.86) are still below the barrier. In addition, the GFI value (0.81) suggests a moderate level of fit between the model-implied covariance and empirical covariance. In addition, the coefficient of determination (R^2) for MR of 0.84 demonstrates that 84% of the variance in learning quality can be explained by school management and teacher competency, so that structurally the model is quite powerful in explaining the variation in MR. Conversely, the R^2 for CP is only 0.20, which suggests that around 20% of the variation in learning achievement may be explained by MR (Table 9). These findings indicate that, although learning quality plays an important role in literacy, numeracy, and character achievement, there are still other factors outside the model that contribute significantly to the variation in learning achievement and potentially need to be considered in the development of models in subsequent studies.

Unlike CB, PLS provides a more limited range of global model fit indices because its main focus is on predictive and component estimation capabilities, rather than on full replication of the covariance matrix. In this investigation, PLS gave an SRMR score (0.08) that was marginally above the threshold. The NFI value (0.83) was likewise below the cut-off. Exact fit indices such as d_ULS (0.88) and d_G (0.44) provide a measure of the distance between the empirical covariance matrix and the model-implied covariance matrix. Exact fit indices such as d_ULS (0.88) and d_G (0.44) provide a measure of the distance between the empirical covariance matrix and the model-implied covariance matrix. In addition, the R^2 for the MR construct was 0.75, indicating that nearly 75% of the variance in MR was explained by the exogenous factors in the model. This result can be classed as high and is backed by a Q^2 value of 0.56, which demonstrates significant predictive relevance for MR. In contrast, the CP has an R^2 value of 0.24 and a Q^2 value of 0.18. These numbers imply that the model is only able to explain roughly a quarter of the variance in learning outcomes, with a poor level of predictive relevance.

GSCA uses a different set of model fit indices but has a similar aim, which is to assess the extent to which the proposed model is able to explain the data structure. In GSCA, the SRMR value (0.06) is below the threshold, indicating relatively minor residuals and a decent approximate fit. The GFI index is likewise high (0.98), indicating that the fraction of variance-covariance explained by the model is fairly big. In addition, the FIT and AFIT indices are 0.64, demonstrating the degree of model fit while considering parsimony.

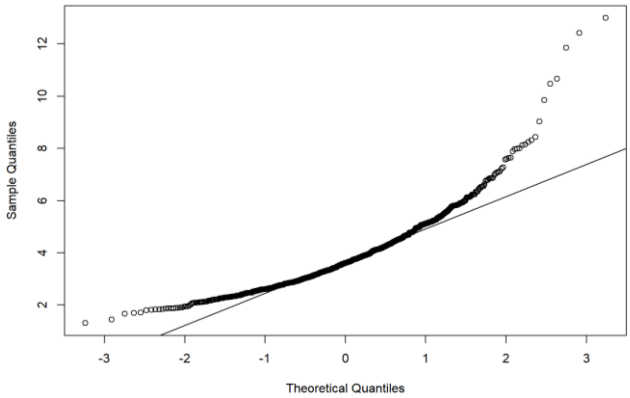
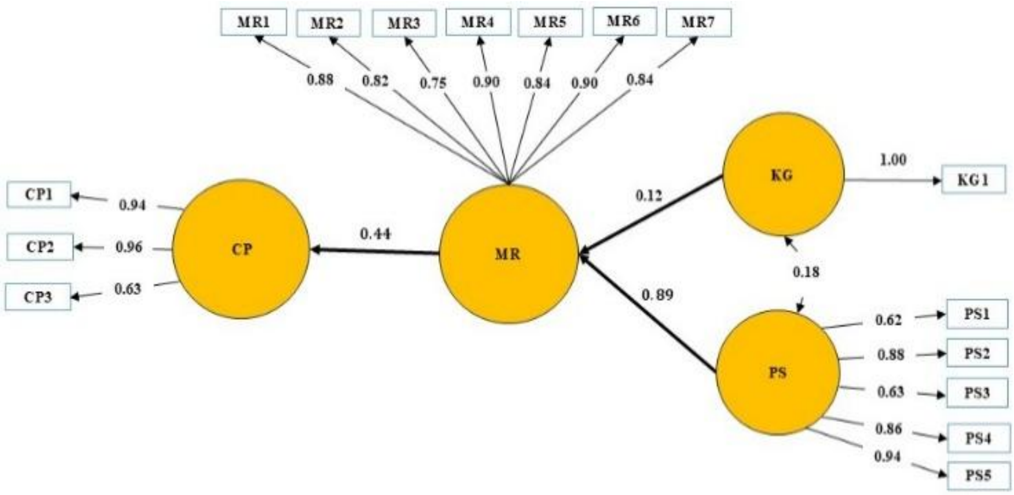
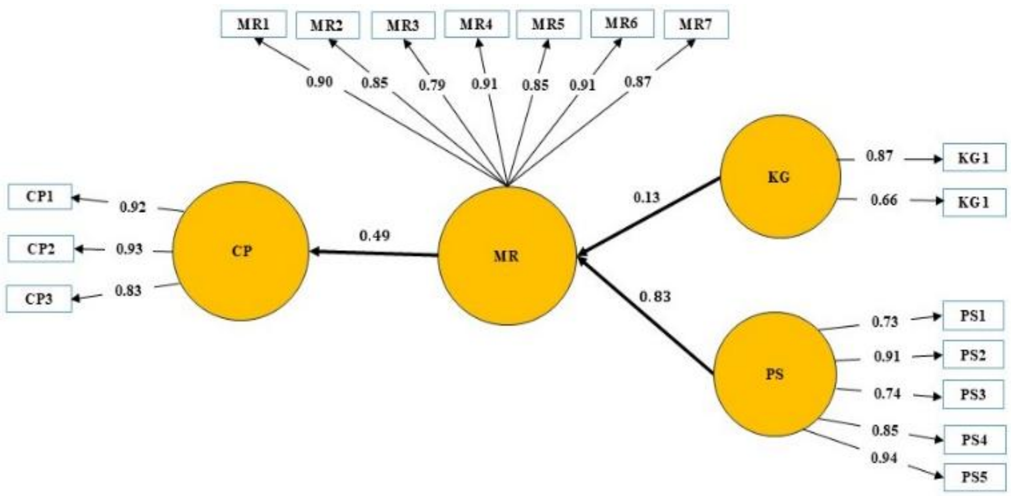


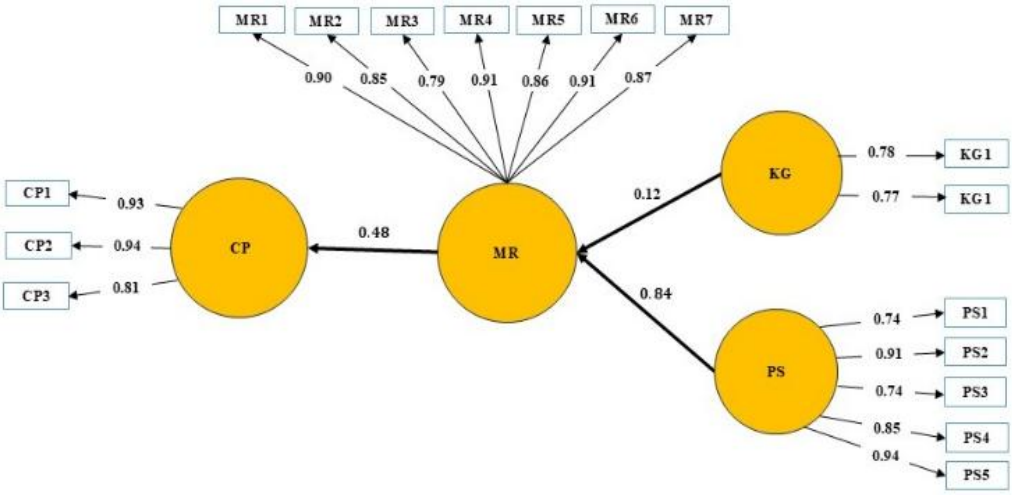
Figure 4. QQ plot of the multivariate normality test



(a)



(b)



(c)

Figure 5. Structural models: (a) CB, (b) PLS, (c) GSCA

Furthermore, the performance of the GSCA model is also evaluated through the model's ability to explain the variation of endogenous constructs. The R^2 for MR is 0.77, indicating that around 77% of the variance in MR can be explained by the exogenous variables in the model, which may be classed as a high level of explanation.

Meanwhile, the CP construct has an R^2 value of 0.23, indicating that the model is only able to explain around a quarter of the variance in learning achievement. This condition is in keeping with earlier findings on CB and PLS; although school administration, teacher competence, and the quality of the learning process contribute to student accomplishment, learning outcomes are still influenced by several additional factors that are not covered in the model. It should be emphasized that the model fit indices in CB, PLS, and GSCA are not fully directly comparable because they depart from various theoretical frameworks and modelling purposes (Figure 5).

3.2 Discussion

The results of this study not only provide a comparative overview of the results of three SEM techniques (CB, PLS, and GSCA) in this data, but also offer various important implications for policymakers, education administrators, and school management.

First, because participatory, transparent, and accountable school administration is the most important factor in determining the quality and relevance of learning, high schools must prioritize improving the quality of teaching by investing resources in strategic initiatives. Schools can encourage parent and student participation, establish anti-bullying rules, implement initiatives to minimize intolerance, and strengthen gender equality. The introduction of these rules aims to directly improve student learning outcomes. In addition, parents and students must actively monitor and evaluate school programs, such as bullying prevention, gender equality improvement, and tolerance building, so that these programs operate effectively and on target. Schools also need to facilitate collaboration between teachers, parents, and students in curriculum development and learning activities so that teaching materials and methods become more contextual and relevant to children's needs. In addition, schools can develop the ability of parents and students to provide constructive feedback to strengthen the effectiveness of participation, resulting in more optimal synergy in supporting the improvement of education quality.

Second, although teacher competence and performance have relatively little impact on the quality and relevance of learning, schools need to raise the proportion of certified instructors and the fraction of teachers with at least a bachelor's degree as a policy priority. National regulations highlight academic degrees and certification as norms of teacher professionalism, making this step imperative. Schools should expand access to online and offline teacher certification programs so that more teachers can participate in tiered training that matches the school's needs. In addition, schools and the government need to ensure that the recruiting method for new teachers meets the minimal level of a bachelor's degree so that the starting quality of educators entering schools is in line with the expected basic competencies.

This data enables schools and local governments to pinpoint strengths and weaknesses in teacher qualifications. They can prioritise schools with few certified or bachelor-qualified teachers for interventions such as additional certification quotas, scholarships, and tiered training. Strengthening teacher competence and performance in this way is expected to support long-term improvements in the quality and relevance of learning. The findings also show that MR is a strong mediator between participatory, transparent, and accountable school management and teacher competence and performance on learning outcomes. In practical terms, school management and teacher development improve student numeracy, literacy, and character primarily by enhancing classroom learning, not by direct effects alone. Schools can raise MR by creating a conducive learning climate, designing engaging activities, giving sufficient attention to students, and aligning the curriculum with student needs. These results suggest that policymakers should treat the improvement of learning quality as a central strategy for raising student outcomes and supporting effective school management and teacher development.

4. CONCLUSIONS

This study applies and evaluates CB, PLS, and GSCA to model the relationship between PS, KG, MR, and CP at the school level based on AN data in Indonesia. The findings of this study provide conclusions from both substantive and methodological perspectives.

First, in all three ways, the structural path exhibits a consistent and substantial pattern. PS has a relatively strong and substantial effect on MR in CB, PLS, and GSCA, while KG has a positive but relatively minor effect on MR, indicating that the KG indicator in this study only reflects some of the key characteristics of teacher competence and performance. MR has a modest and considerable effect on CP, indicating its position as a major mediator. The comparatively low R^2 values for CP in all models indicate that learning outcomes are also influenced by other factors at the school, teacher, student, and contextual levels that are not covered in the model.

Second, applying CB, PLS, and GSCA reveals both convergent results and major methodological variances. All three approaches give essentially comparable substantive outcomes and show appropriate convergent validity and reliability for most constructs. However, CB suggests a discriminant validity difficulty between PS and MR, with very significant latent correlations that violate the Fornell–Larcker criterion; therefore, the distinct effects of PS and MR must be interpreted cautiously. Model fit indices also differ: CB focuses on covariance-based fit (SRMR, Robust RMSEA, Robust CFI/TLI, NFI, GFI), PLS on predictive performance (SRMR, NFI, d_ULS, d_G), and GSCA on approximate fit and component performance (SRMR, FIT, AFIT, GFI). In all three, endogenous variance is quantified by R^2, and in PLS, also Q^2. These distinctions represent diverse modelling philosophies: covariance reproduction, prediction focus, and component-based structural modelling; therefore, technique choice should correspond with study aims and data features.

Third, this study has important implications for future policy and research. Substantively, this study shows that strengthening participatory, transparent, and accountable school management is a key factor in improving the quality and relevance of learning, which in turn improves student learning outcomes in numeracy, reading, and character; increasing the proportion of certified and bachelor's degree-holding teachers remains important, but must be supported by policies that directly target classroom practices. Methodologically, future research should use more comprehensive indicators of teacher competence and performance, utilize additional data sources to reduce potential bias, and expand analysis to better multilevel and longitudinal models that capture the dynamics of schools, classrooms, and students over time.

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