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Comparison of cognitive achievement model: teacher learning character and student learning character with school climate moderation, PLSPredick approach

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This study examines the interaction between teacher learning character, student learning character, and school climate in influencing students' cognitive achievement. Data from 1,057 high school students in North Maluku was analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. This study explores the direct relationship and mediation between variables. The results showed that teacher competence and innovation significantly improved teacher efficacy (R^2 = 0.576) and teacher performance (R^2 = 0.670) despite its direct influence on students' low cognitive achievement (R^2 = 0.024). In contrast, student character, such as learning style, learning concepts, and academic perseverance, had a more direct and mediating influence on cognitive outcomes, with academic perseverance as the primary mediator. In addition, the school climate moderates the relationship between teacher innovation and cognitive achievement, which shows a selective yet essential role. These findings emphasize the importance of encouraging teacher innovation, increasing student perseverance, and building a supportive school environment to optimize educational outcomes. This study highlights the complexity of the interaction between teaching, learning, and environmental factors and suggests the need for integrated strategies to improve students' cognitive achievement.

KEYWORDS

teacher character, student character, cognitive performance, school climate, PLSPredick

1 Introduction

Students' cognitive achievement is one of the leading indicators in determining the success of the educational process, which is the ultimate goal of various education systems worldwide. This achievement reflects how students understand, master, and apply knowledge across multiple learning contexts(Alruwais and Zakariah, 2023; T. Zhang et al., 2023). Factors that affect cognitive achievement include internal and external elements of students, including learning ability, motivation, and support from the educational environment (Dadandı and Yazıcı, 2024; Shi and Qu, 2022). Although many studies have explored the influence of individual variables such as motivation and learning strategies on cognitive achievement, there has not been much that has discussed in depth the combination of teacher learning character and student learning character as the primary predictor variable (de Bofarull, 2019; Wagner et al., 2020). To understand how the interaction between these internal and external factors can affect student learning outcomes. In addition, it is essential to explore the role of teachers in creating a learning environment that supports students' cognitive development.

The role of teachers in supporting students' cognitive achievement is very significant, primarily through competence, efficacy, performance, and innovation in learning. Teacher competence relates to pedagogic and professional abilities that directly affect how they deliver material to students (Channa et al., 2024; Fauth et al., 2019; Kaiser and König, 2019). Teacher efficacy describes teachers' confidence in helping students achieve academic success, which has been shown to impact learning outcomes (Floyd, 2023; Husain et al., 2023; Javidanmehr and Anani Sarab, 2019). Teacher performance and innovation are essential in creating a dynamic and engaging learning atmosphere (Shelty et al., 2023). Some studies show that although teachers have good competence and efficacy, their impact on student achievement is inconsistent, primarily if a conducive school climate does not support it. This indicates the need for a more integrated approach to understanding how these factors interact.

Students learning character is essential in determining their academic success, primarily through learning style, conception, and academic persistence(Genith Isaza Domínguez et al., 2025; Sejdiu Shala et al., 2024). The learning style reflects the unique way students process information, which relates to the cognitive and metacognitive strategies used to understand, remember, and apply knowledge. Adaptive learning styles can increase student engagement in learning and lead to better cognitive achievement (Halkiopoulos and Gkintoni, 2024). Additionally, constructive conceptions of learning, such as the understanding that learning is an active and ongoing process, have been shown to encourage students to develop more effective learning strategies (Carpenter et al., 2022; Fixen, 2021). Therefore, a learning approach that follows students' learning styles is crucial to supporting their success.

The conception of learning is crucial in shaping how students understand and undergo the learning process. Students who believe that learning is a process that involves exploration and reflection tend to be more successful in facing academic challenges (Cai et al., 2021; Lowyck et al., 2004). These beliefs also influence how they use learning resources and face obstacles during the learning process (Dewi et al., 2022; Kandaga et al., 2023). In addition, students with a positive conception of learning are more likely to develop self-confidence and self-efficacy in achieving their academic goals (Cohen and Katz, 2024; Khine and Nielsen, 2022). However, without the support of a conducive learning environment, the positive effects of this conception of learning may not be fully realized, so there is a need for collaboration between teachers, students, and other elements of the school environment (Kaldırım and Tavşanlı, 2018; Shand and Goddard, 2024).

Academic persistence contributes significantly to students' cognitive achievement, especially in helping them stay motivated to face various challenges (Torgrimson et al., 2021; You, 2018). This persistence reflects the student's ability to remain focused on their academic goals despite obstacles, such as time pressure or lack of resources(Pinugu and Ouano, 2022; Xavier and Meneses, 2022). Academic persistence positively correlates with deep learning strategies and superior learning outcomes (Cents-Boonstra et al., 2021; Thompson and Lake, 2023; Vettori et al., 2020). The interaction between students' academic persistence and other factors, such as teacher character and school climate, is still underexplored. To bridge that gap by exploring how academic persistence can be strengthened through collaboration between students, teachers, and a supportive school environment.

The school climate as moderation plays an essential role in creating an environment that supports the relationship between teacher and student character toward cognitive achievement (Shumakova et al., 2023; Teng, 2020). A positive school climate, which includes physical, social, and academic aspects, has been shown to increase student engagement in learning as well as support teacher-teaching effectiveness (Al-Zu'bi et al., 2024; Grazia and Molinari, 2023; Rinchen, 2020). Studies conducted by Wei1 et al. (2024) demonstrate that a supportive environment significantly impacts student motivation, teacher efficacy, and learning outcomes (Cai and Lombaerts, 2024). However, research that integrates school climate as a moderation variable in models involving teacher and student characters is still minimal, thus opening up opportunities to make greater theoretical and practical contributions.

This study aims to compare the teacher's learning character model with the student's learning character on cognitive achievement influenced by school climate as a moderation in the research. The use of the PLS-SEM (Partial Least Squares Structural Equation Modeling) approach was chosen because it has the advantage of handling models with many latent variables and indicators, especially in studies that are exploitative and focus on predicting the relationship between variables(Hair and Alamer, 2022; Zeng et al., 2021). Strengthening model predictions are used by PLS-Predict to evaluate the model's predictive ability to provide in-depth insight into the predictive power of each variable in influencing students' learning outcomes (Liengaard et al., 2021; Sharma et al., 2023). In addition, this method also makes it possible to analyze the relationship between variables and identify relevant direct, indirect, and moderation influences in understanding the dynamics of educational factors that can affect learning achievement (Caemmerer et al., 2024; Salma et al., 2020).

By focusing on teacher learning characteristics, such as teacher competence, teacher innovation, and teacher efficacy, as well as student learning characteristics, including learning style, academic persistence, and learning conception, this study tries to describe how the interaction between these elements plays a role in influencing students' cognitive achievement. The proposed model is expected to provide a more holistic understanding of the factors that affect students' cognitive achievement and enrich existing theories regarding learning and teaching. By analyzing dynamically interacting variables, this study tested that H1: The teacher's learning character model has a significant influence on students' cognitive achievement, H2: The student learning character model has a significant influence on students' cognitive achievement, H3: The student learning character model has a stronger predictive ability on students' cognitive achievement compared to the teacher's learning character model.

Students' cognitive achievement is one of the key indicators in assessing educational success, reflecting the extent to which students can understand, master, and apply knowledge in a variety of learning contexts (Tikhomirova et al., 2020; Tikhomirova et al., 2021). This achievement is influenced by many internal and external factors (He et al., 2021). Teachers' learning characteristics, including competence and skills in designing and managing learning, greatly influence student achievement (Daniel et al., 2024; Lazo, 2024). In addition, students' learning characteristics, such as learning style, academic persistence, and learning conception, also contribute significantly to their ability to achieve optimal cognitive outcomes (Gordeeva and Sychev, 2024; Wu et al., 2024). The school climate, which includes the learning environment's social, emotional, and physical aspects, acts as a moderator that can strengthen or weaken the influence of these characters on students' academic achievement (Voight et al., 2024). A positive and supportive environment can enhance the relationship between teacher competence and student academic achievement (Konstantinidou and Scherer, 2022).

1.1 Teacher's learning character

The learning character of a teacher is the attitude, values, and skills an educator possesses in carrying out the learning process (Muzakkir and Razak, 2024; Zhou et al., 2024). There are several components of teacher learning character in the form of attitudes, competencies, and skills (Salamah, 2024). Teachers' attitudes, especially in the form of teacher self-efficacy, play an essential role in increasing learning effectiveness and student learning outcomes. Studies conducted by Ke and Razali (2024) show that teacher efficacy positively correlates with teacher competence and performance in school. Moreover, Krasniqi and Ismajli (2022) Found that teacher efficacy can moderate the relationship between teacher competence and performance and strengthen teachers' confidence in managing the classroom and implementing innovative learning strategies.

Teacher competence is a set of knowledge, skills, and attitudes an educator possesses to carry out his duties procedurally and effectively (Moreira et al., 2023). Teacher competence consists of several main components that support activities in the teaching process, namely pedagogic competence, professional competence, social competence, and personality competence (Hakim and Firmansyah, 2024; Tang et al., 2021). These four components are essential to improve the quality of learning and the effectiveness of teachers in educating (Azkiyah and Mukminin, 2023; Creemers and Kyriakides, 2013). Teacher competence has a significant influence on students' cognitive achievement because it determines the effectiveness of the learning process in the classroom (König et al., 2021; Zheng et al., 2025). Teachers with good competence can design learning that suits student needs, manage classes effectively, and use the right learning tools and evaluation methods to improve student learning outcomes (Divoll and Lastrapes, 2024). School climate as a moderation factor is essential in strengthening the relationship between teacher competence and students' cognitive achievement (Teng, 2020). A physical environment and an academic environment that supports students' academic achievements (Edgerton and McKechnie, 2023; Liu et al., 2022). The environment encourages academic engagement, emotional safety, and social support to create optimal conditions for teachers to effectively apply their competencies in the learning process (Li et al., 2022; Shao et al., 2025; Thomas and Nair, 2023; Zhang and Yang, 2021).

Teacher performance is the level of effectiveness of an educator in explaining their duties, including planning, implementing, and evaluating learning, as well as their interaction with students (Bantoc and Yazon, 2023). Optimal teacher performance reflects mastery of learning methods, well-developed classroom management, and the ability to motivate students (Alasmari and Althaqafi, 2024; Sarfraz et al., 2022; Wulandari and Sugiyono, 2021). Teacher performance directly affects student collective achievement, where teachers have high performance that can effectively improve concept understanding, learning motivation, and cognitive achievement (van Dijk et al., 2019; Victoriano et al., 2022). School climate as a moderation factor can strengthen the relationship between teacher performance and student achievement by creating a supportive, safe, and conducive learning environment (Longobardi et al., 2022; Teng, 2020). Studies conducted by Zynuddin et al. (2023) show that a positive school climate, such as more effective teaching, thus increases absorption and cognitive achievement. Therefore, improving teacher performance must be accompanied by efforts to create a good school climate to maximize the positive impact on students' collective restoration.

Teacher innovation is the ability of an educator to develop and implement learning strategies, methods, and technologies creatively and effectively to improve the quality of learning and student learning outcomes (Yu et al., 2021). Practical teacher innovation is the application of new ideas, practices, or objects in learning designed to improve teaching effectiveness and learning outcomes (Syamsul et al., 2022). Teachers designing learning models and learning media are a substantial dimension in influencing classroom learning success (Akbar et al., 2023; Hajovsky and Chesnut, 2025). The application of teacher innovation can have a positive effect on student learning outcomes because it can increase student involvement, strengthen concept understanding, and create a more interesting and interactive learning experience (Fletcher et al., 2020; Maksimović et al., 2022; Pan and Liu, 2025). School climate as moderation supports or inhibits teachers' innovation in improving students' cognitive achievement (Kundu and Roy, 2023; Zhao et al., 2023). Studies conducted by Pan and Liu (2025) show that a collaborative school environment that is open to technology and supports teacher creativity can strengthen the relationship between innovation in learning and students' academic outcomes. Therefore, schools that create a culture that supports teacher innovation can make teachers more flexible in developing learning methods that positively impact students' cognitive performance.

1.2 Student learning character

The character of student learning includes various elements that play a role in influencing the way students learn and the academic results achieved (Kang, 2023; Pan and Liu, 2025). The learning character of students is influenced by various intrinsic and extrinsic factors that form cognitive and affective patterns in the learning process (Hajovsky et al., 2023). Conceptually, the learning character includes several main elements, including learning styles, academic persistence, and learning conceptions (Gordeeva and Sychev, 2024; Jebbari et al., 2022; Pinugu and Ouano, 2022). Learning style refers to individual preferences in absorbing, managing, and organizing information that can be categorized into active and accommodating learning styles (Gordeeva and Sychev, 2024). The conception of learning refers to the student's understanding of the essence of learning, including the teacher's listening-based approach and problem-solving skills (Liu, 2024). As a determinant factor of student academic success, academic persistence is closely related to student commitment and resilience in facing learning challenges (Gabi and Sharpe, 2021; Năstasă et al., 2022). These three elements interact dynamically and affect students' learning abilities and achievements. A comprehensive understanding of learning characteristics can be used to develop more effective learning strategies to improve students' cognitive achievement.

Learning style is an individual's pattern or tendency to absorb, manage, and apply information in the context of learning (Mozaffari et al., 2020). This concept encompasses a wide range of cognitive, affective, and conative dimensions that make up each student's unique approach to cognitive achievement (Dadandı and Yazıcı, 2024; Mangaroska et al., 2022; Rieser and Decristan, 2023). Learning styles are categorized based on different models, such as the experiential learning model, which groups individuals into convergent, divergent, assimilative, and accommodating learning styles, and the WARK (visual, auditory, reading, kinesthetic) model, which applies sensory modalities in the learning process (Dantas and Cunha, 2020; Grotek, 2024). Learning styles play an essential role in shaping learning strategy activities applied by students so that they directly impact students' academic achievements (Dutsinma et al., 2018; Kuttattu et al., 2019; Ma, 2024). Students who understand and apply learning styles that suit their cognitive styles and preferences tend to assimilate information better, improve critical thinking skills, and strengthen memory and problem-solving (Deagon, 2023). Developing learning strategies that are in harmony with the variety of student learning styles is crucial in improving the quality of learning and student collective achievement (Bhat et al., 2021; Magodi et al., 2023). The school climate, which includes social, academic, and emotional aspects in the educational environment, moderates the relationship between learning styles and student collective achievement (Teng, 2020). A supportive environment with the support of teachers, peers, and adequate learning facilities can improve students' cognitive achievement (Chen et al., 2022; Rijal Abdullah et al., 2024). Education policies that focus on enhancing a positive school climate are crucial in maximizing the impact of learning styles on students' cognitive achievement outcomes.

The conception of learning is an individual's understanding and belief about the learning process, including how knowledge is obtained and applied (Murtonen and Lehtinen, 2020; Pinto et al., 2018). Learning can be categorized as a deep understanding or a superficial approach, where the deep approach is more oriented toward understanding the concept as a whole (Biggs et al., 2022). The conception of learning has a significant impact on students' cognitive achievement. Students with a more in-depth conception of learning tend to use more effective learning strategies, thus contributing to higher academic achievement (Ota et al., 2023; Pinto et al., 2018; Vettori et al., 2020). In contrast, superficial conceptions of learning are often associated with lower academic outcomes because they focus only on memorization without deep understanding (Duan, 2022; Kerrigan and Kwaik, 2024; Thompson and Lake, 2023; Vettori et al., 2020). In addition to the concept of learning, the climate is also a factor that can affect the improvement of cognitive achievement through the conception of learning (Erdem and Kaya, 2024; Zysberg and Schwabsky, 2021). School climate is a moderation effect that can strengthen or weaken the relationship between learning conception and cognitive achievement (Maxwell et al., 2017; Zhang and He, 2025). A supportive school climate, such as physical conditions in the form of facilities and resources as well as academic conditions, can encourage students to develop deep learning perceptions that can have an impact on improving cognitive achievement (Rance et al., 2023; Villarreal Arroyo et al., 2023).

Academic persistence is the persistence and effort students make to achieve their academic goals, especially when facing challenges or difficulties in learning (Chue and Lim, 2024). Academic persistence reflects traits such as resilience to obstacles, motivation, internal and the ability to overcome failure with continuous effort (Putwain et al., 2024; Tang et al., 2019). Academic persistence positively correlates with cognitive achievement (Gordeeva and Sychev, 2024). Students with a high level of persistence tend to be better able to manage commitment, control, and challenge strategies in the face of better learning strategies (Studer et al., 2020; Xu et al., 2024). In addition, academic persistence also affects student engagement in learning, indirectly improving cognitive achievement (Gordeeva and Sychev, 2024; Maamin et al., 2021). The climate plays an important role in strengthening or weakening the impact of academic persistence on students' cognitive reproduction (Verner-Filion, 2023). A supportive school climate, such as physical and academic conditions, can increase the positive effects of academic persistence on cognitive achievement (López, 2023). On the other hand, a less conducive school climate can hinder the development of academic perseverance and reduce the positive impact on cognitive achievement.

1.3 School climate as moderation

School climate refers to the social, emotional, and physical atmosphere formed within the educational environment, which affects students' learning experience and development. The school climate includes a social and emotional atmosphere built through interactions between students, teachers, and staff (Kearney et al., 2020; Lewno-Dumdie et al., 2020; Shumakova et al., 2023). A favorable climate, where there is a sense of security and mutual respect, is directly related to academic success and the development of student behavior (Berkowitz and Ben-Artzi, 2024; Daily et al., 2020; Ellis et al., 2022). The school climate is influenced not only by social factors but also by the physical condition of the school environment, such as the quality of facilities and the cleanliness of the classroom (Kearney et al., 2020; Kumar et al., 2024; Martenies et al., 2022). Good physical condition is essential to increase student motivation and create a supportive atmosphere for learning (Fisher and Africa, 2025). Academic conditions affect the quality of education, including teaching management, the way students are encouraged to participate, and the support provided by teachers (González et al., 2021; Mariscal-Camacho et al., 2024). He emphasized that positive interaction between teachers and students is essential in creating an academic climate that supports learning achievement (Pimpalkhute et al., 2023; Poling et al., 2022). The school climate is a combination of healthy relationships between students and teachers as well as an environment that supports students' social, emotional, and academic development (Kearney et al., 2020; La Salle et al., 2021; Rizzotto and França, 2022; Sethi and Scales, 2020). A healthy school climate contributes to academic outcomes and the development of social and emotional skills that are crucial for students' futures (Berkowitz and Ben-Artzi, 2024; Daily et al., 2020; Thapa and Cohen, 2023). Overall, school climate encompasses the physical, social, and academic dimensions that are interrelated and essential for creating an optimal environment for student growth and learning.

The school climate includes influencing the learning process and student development, both physically and academically (Capp et al., 2020; Lewno-Dumdie et al., 2020; Moore et al., 2022). Physical conditions in a school's climate refer to factors such as physical facilities, cleanliness, security, and classroom comfort, all of which have a significant influence on a student's learning experience (Razali et al., 2024; Sultana et al., 2023; Tharim et al., 2023). School cleanliness and physical order are essential in creating an environment conducive to learning (Rajbhandari-Thapa et al., 2022; Uleanya, 2020). Good facilities with students' perception of the school as a safe and supportive place, which in turn encourages higher academic engagement (Coyle et al., 2022). Academic conditions include the quality of teaching, the interaction between teachers and students, and the expectations given by the school to students' academic achievement (Hashim Jabur, 2024; Luo et al., 2025; Ouwehand et al., 2022). A positive academic climate is created when teachers provide meaningful teaching, provide constructive feedback, and encourage active student participation (Fraser, 2023). A healthy relationship between teachers and students is essential in creating a supportive academic climate (Davis and McQuillin, 2023; Wang and Xian, 2024; Zhang, 2025). Students' social and emotional involvement in learning is key to building confidence and high academic achievement (Guterman and Neuman, 2022). The quality of social interaction in the classroom can reinforce the academic conditions, where students feel valued and encouraged to thrive (García-Moya and García-Moya, 2020). Thus, a good school climate depends on adequate physical facilities and how academic interaction is carried out. The combination of supportive physical conditions and high academic quality creates an all-around atmosphere, significantly improving student learning outcomes.

1.4 Partial least squares structural equation modeling (PLS-SEM)

Partial Least Squares Structural Equation Modeling (PLS-SEM) is a statistical technique widely used to test the relationships between complex latent variables, especially in research involving many factors. PLS-SEM is a valuable tool for testing theoretical models involving relationships between variables that are difficult to measure directly, such as education (Hair et al., 2019). This technique allows for the analysis of more straightforward to very complex models with many variables and overcoming the data problem that does not meet the assumptions of normal distribution. PLS-SEM enables the measurement of relationships between variables with greater precision, even in smaller samples and with more diverse data (Gefen et al., 2011). This approach is beneficial for theoretical models that are still developing, allowing flexibility in unearthing new and complex relationships in the field of education(Chin et al., 2003). PLS-SEM in research involves many non-linear cause-and-effect relationships, such as those often found in interactions between teachers, students, and educational outcomes (Sarstedt et al., 2021).

PLS-SEM is relevant in education because it can handle variables that are challenging to measure directly, such as the quality of learning or the school climate. This technique allows researchers to map complex relationships between educational policies, teaching quality, and student learning outcomes (Henseler et al., 2015). PLS-SEM allows for better models for measuring abstract dimensions in education, such as non-cognitive skills that affect students' academic success (Sarstedt et al., 2021). PLS-SEM provides an advantage in analyzing models with many latent variables, facilitating a better understanding of the variables that interact with each other in the education system (Rigdon et al., 2017). The advantages of PLS-SEM lie in its ability to overcome problems with small sample sizes and data that do not always meet the normal distribution, which is often the case in educational research with limited populations (Urbach and Ahlemann, 2010). PLS-SEM helps researchers to identify strong relationships and relevance between factors that affect educational outcomes, such as the influence of curriculum or the quality of teacher-student relationships on student achievement.

2 Materials and methods

This study used a quantitative design using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method to analyze the relationship between latent variables and predict the proposed model. The PLS-SEM method was chosen for its ability to handle complex models with many latent variables, including direct influence, mediation, and moderation (Byon and Jang, 2024; Sarstedt and Moisescu, 2024). This method is very suitable for exploratory research that aims to understand the relationship between various factors that interact with each other, namely teacher learning characteristics, student learning character, and school climate moderation on cognitive achievement.

PLS-SEM has the main advantages of handling data that is not normally distributed and smaller sample sizes (Hair et al., 2019). In addition, this method focuses more on the predictive aspect than on causality inference, allowing the analysis of complex relationships between latent variables with a prediction-based approach (Avkiran, 2018; Hair and Alamer, 2022; Lin et al., 2020). CB-SEM is superior in testing theory-based causal relationships, but this approach is more suitable if the model is theoretically established (Rigdon et al., 2017). This study used PLS-Predict to evaluate the model's predictive capabilities (Chin et al., 2020; Sharma et al., 2023). Then, the teacher's learning character model will be compared with the student learning character model, which is influenced by the school climate and moderates cognitive achievement. Therefore, this approach is appropriate for exploring such interactions.

2.1 Instrument validation and reliability testing

The research instruments used are valid and reliable. Validity and reliability tests are carried out before the principal analysis. Test the validity of the instrument's content through expert judgment, where 5 (five) experts assess the suitability of the content with the concept being measured. This assessment was analyzed using Aiken's index, which shows that the item has a high validity category of 96.66%. After going through a minor revision based on the input of experts, the instrument was then empirically tested, and the empirical test data was then cleaned outlier data. Out of 150 empirical test respondents, as many as 15 data (respondents) were eliminated because they had significant univariate outlier values. The Mahalanobis distance analysis showed no multivariate outliers were detected, and the normality test confirmed that the data was distributed normally multivariate. The results of the bivariate correlation test between Mahalanobis distance and Chi-Square showed a very high relationship

($r = 0.0994$, $p < 0.01$), which indicated that the data distribution was suitable for further analysis.

At the empirical validity test stage, the analysis showed that 6 out of 26 items of the cognitive achievement variable instrument were declared misfits, so they were not valid for further measurement. While in the other variables, all items met the validity criteria. Reliability tests are performed to ensure internal consistency between items using Cronbach's Alpha and item-rest correlation. The analysis showed that all items had a high-reliability level above 0.8 for all variables. This indicates that internal consistency is good and can be relied on in subsequent measurements. Furthermore, there are 100 instrument items for all variables in the field test for research data collection (Table 1).

2.2 Sample and data collection

The sample of this study consisted of 1,057 high school students from 11 schools in North Maluku Province, Indonesia. Questionnaires are used to collect data using Google Forms, and questionnaire books are distributed. The scale used in assessing the questionnaire items is a Likert scale with an interval from 1 (disagree) to 4 (strongly agree).

2.3 Data analysis

This research was conducted by distributing 80 statement items and 20 cognitive achievement test items to 1,057 samples. To test the validity and reliability of the instrument empirically. The first stage in the analysis of field test data is to carry out a prerequisite test, which includes an outlier test and a normality test. Outlier tests are performed to identify and remove extreme data affecting the analysis results. Nineteen data were eliminated because they were detected as univariate and multivariate outliers. The data remaining after elimination were 1,037 samples and were free of outliers, allowing for further analysis. The normality test analyzed the relationship between the Mahalanobis distance and Chi-Square, which showed multivariate standard distributional data. The results of the bivariate correlation showed a significant value of 0.01 with a correlation coefficient of 0.989, indicating that more than 50% of the data met the standard distribution criteria (Figure 1).

Data analysis using Smartpls4 involves systematic stages to ensure the research model is valid and can be interpreted. The first stage is to determine the research model, where the researcher identifies the latent variables (constructs) and the indicators used to measure them. This step includes the development of a conceptual model that explains the relationship between exogenous and endogenous variables and the type of measurement (reflective or formative). It is also essential to ensure that the relationship between variables follows the underlying theory. Model measurements are carried out to ensure the validity and reliability of the construct for reflective models (Figure 2).

A direct influence structural model was performed to test the relationship between latent constructs. Path coefficients are evaluated using the bootstrapping method and mediation test, and the researcher evaluates whether the mediating variable bridges the relationship between independent and dependent variables. This stage involves testing direct effects and indirect effects. The moderation test aims to assess whether the moderator variable affects the effect between two constructs. Moderation can be quantitative, which changes the strength of the relationship, or qualitative (Table 2). The criteria for structural model compatibility are described in Table 3 as follows:

3 Results

3.1 Teacher learning character model

The validity test in the PLS analysis uses the outer loading size or loading factor. Outer loading measure is a statistical measure used to see how far the indicator reflects the measurement of variables or the extent to which the indicator is valid. The prerequisite outer loading value of > 0.70 is considered significant (Hair et al., 2019), while values between 0.40–0.70 can be regarded as if the contribution is still relevant (Chin, 1998). Table 4 shows that the outer loading value meets the level of validity following the standard (Tables 5–10).

TABLE 1 Codes for questionnaire items.

Area	Variable	Variable code									
Moderation	School climate	IS1	IS2	IS3	IS4	IS5	IS6	IS7	IS8	IS9	IS10
Teacher learning characteristics	Teacher competency	KG1	KG2	KG3	KG4	KG5	KG6	KG7	KG8	KG9	KG10
	Teacher efficacy	EG1	EG2	EG3	EG4	EG5	EG6	EG7	EC8	EG9	EG10
	Teacher performance	KiG1	KiG2	KiG3	KiG4	KiG5	KiG6	KiG7	KiG8	KiG9	KiG10
	Teacher innovation	IG1	IG2	IG3	IG4	IG5	IG6	IG7	IG8	IG9	IG10
Student learning character	Learning style	LB1	LB2	LB3	LB4	LB5	LB6	LB7	LB8	LB9	LB10
	Learning concepts	KB1	KB2	KB3	KB4	KB5	KB6	KB7	KB8	KB9	KB10
	Academic persistence	KA 1	KA2	KA3	KA4	KA5	KA6	KA7	KA8	KA9	CA10
School climate		IS1	IS2	IS3	IS4	IS5	IS6	IS7	IS8	IS9	IS10
Cognitive performance		26 item									

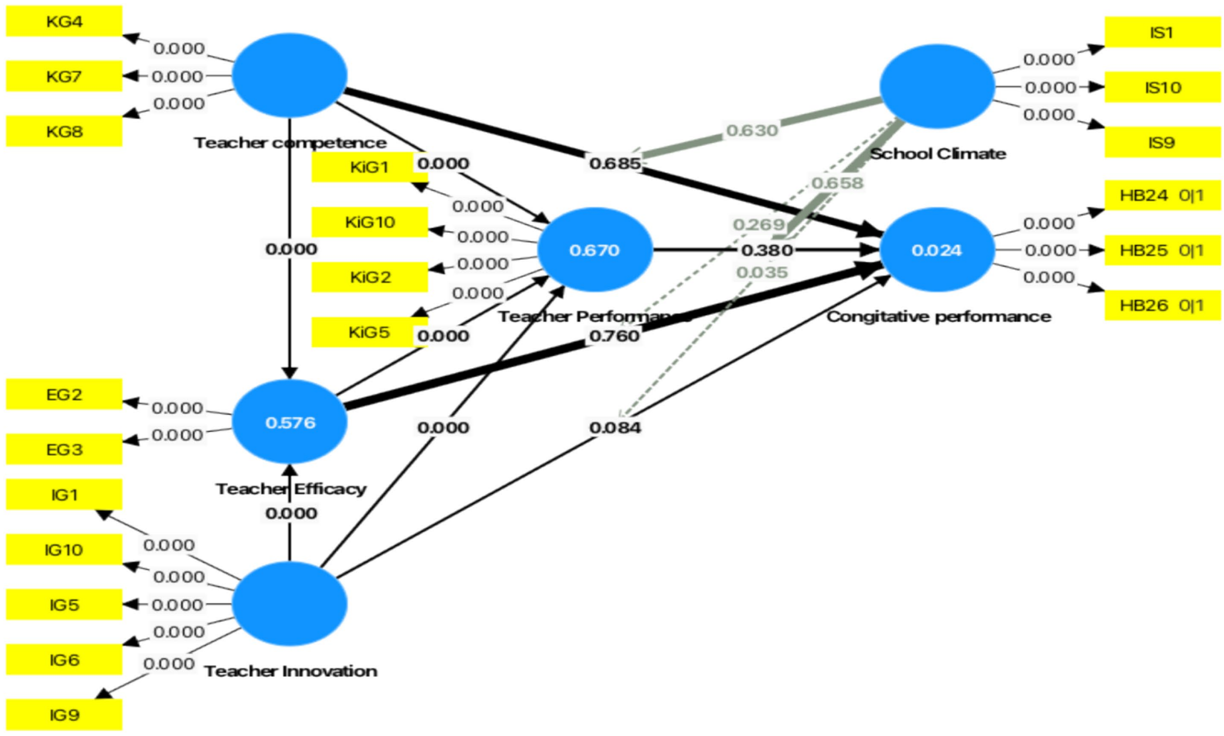

FIGURE 1
Path coefficient prediction model.

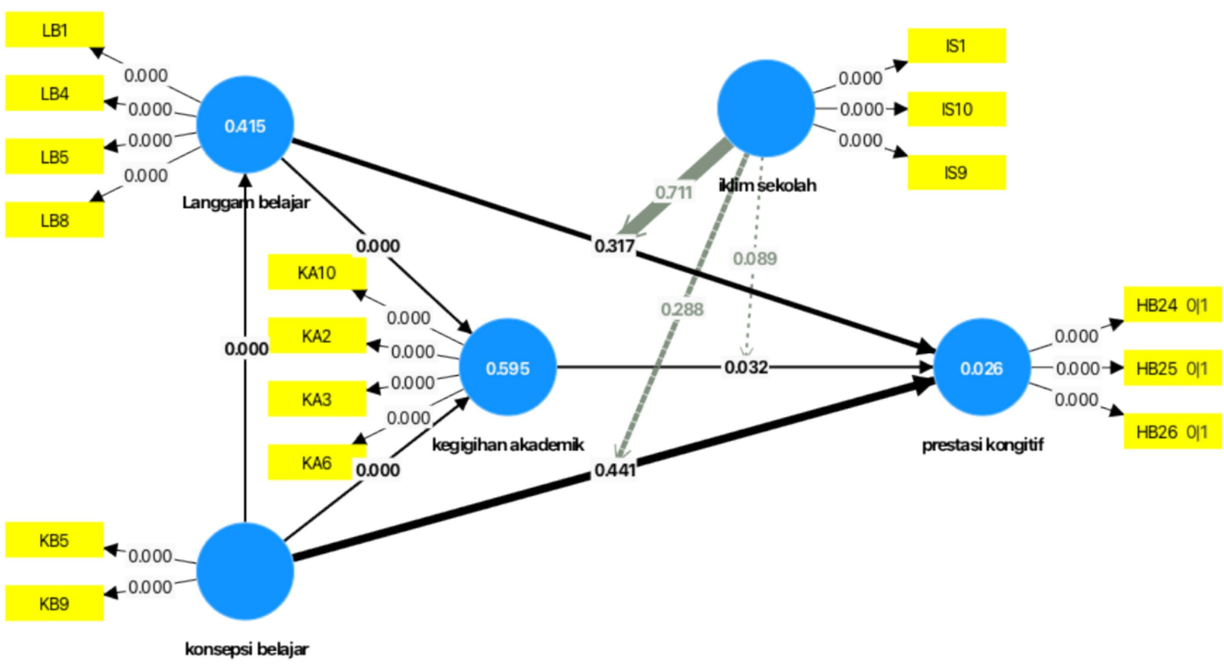

FIGURE 2
Path coefficient prediction model.

Construct reliability evaluation is based on two main measures, Cronbach's Alpha and Composite Reliability (rho_a), which are used to measure the internal consistency of indicators in a construct. According to (Hair et al., 2017), Cronbach's Alpha and Composite Reliability values greater than 0.70 indicate that the construct has good reliability, i.e., the indicators used to measure the construct support each other and are consistent in conveying information. It is described in the following Table 4.

TABLE 2 Evaluation of model measurements.

Criteria	Aspects that are measured	Evaluation method	Ideal value	Reference
Reflective model	Indicator validity	Outer loading	>0.70	Hair et al. (2019)
	Convergent validity	Average variance extracted (AVE)	>0.50	Hair and Alamer (2022)
	Construct reliability	Composite reliability (CR)	>0.70	Hair and Alamer (2022)
	Discriminant validity	Fornell-Larcker criterion or HTMT ratio	HTMT < 0.85 (more sensitive)	Henseler et al. (2015)
Formative model	Multicollinearity	Variance inflation factor (VIF)	< 5	Diamantopoulos and Siguaw (2006)
	Significance of outer weights	Bootstrap	Significance value (*p*-value) $p < 0.001$	Hair et al. (2017)

TABLE 3 Evaluation of structural models.

Aspect	Evaluation model	Criteria	Reference
Structural model	Path coefficients use bootstrapping	*p*-value < 0.05	Hair (2020)
	Coefficient of determination (R^2)	Weak (≥ 0.02), Moderate (≥ 0.15), Strong (≥ 0.35)	Hair et al. (2017)
	Predictive effect (Q^2) using bootstrap	$Q^2 > 0$ indicates predictive relevance	Henseler et al. (2015)
Mediation test	Direct line (*direct effect*) and indirect (*indirect effect*) using bootstrapping	*p*-value < 0.05 and confidence interval (bias-corrected) valid	Ogbeibu et al. (2021)
Test moderation	Test the significance of the interaction using bootstrapping	*p*-value < 0.05	Hair (2020)
	Moderation effect size (f^2)	Weak (≥ 0.005), Moderate (≥ 0.01), Strong (≥ 0.025)	Hair (2020)

TABLE 4 Outer loading, composite reliability, and average variance extracted.

Variable	Measurement items	Outer loading	Cronbachs alpha	Composite reliability	AVE
Teacher competency	KG4	0.742	0.726	0.747	0.643
	KG7	0.832			
	KG8	0.828			
Teacher efficacy	EG2	0.908	0.798	0.799	0.832
	EG3	0.917			
Teacher innovation	IG1	0.792	0.884	0.886	0.683
	IS10	0.846			
	IG5	0.819			
	IG6	0.837			
	IG9	0.837			
Teacher performance	KiG1	0.720	0.734	0.750	0.555
	KiG10	0.816			
	KiG2	0.706			
	KiG5	0.734			
School climate	IS1	0.865	0.751	0.797	0.660
	IS10	0.813			
	IS9	0.757			

3.1.1 Evaluation of the structure model (inner model)

3.1.2 Evaluation of predictive abilities

R-square is a measure that describes how much of the proportion of variance of dependent (endogenous) variables can be explained by independent (exogenous) variables in a model. In the analysis using Partial Least Squares-Structural Equation Modeling (PLS-SEM), the R-square value is the leading indicator in assessing the model's predictive power. The criteria for evaluating the R-square value consist of three main categories: a value of >0.75 or more is considered substantial, a value between 0.50-0.75 is considered moderate, and a value between 0.25-0.50 is considered weak. If the value < 0.25, the model's capabilities are considered weak (Musyaffi et al., 2022).

The PLSPredict evaluation table shows the results of testing the predictive ability of the PLS-SEM model using Q^2 predict, RMSE

TABLE 5 Direct influence testing.

	Original sample (O)	*T* statistics (|O/STDEV|)	*p* values	Information
School climate - > Cognitive performance	-0.044	1.906	0.057	Insignificant
Teacher efficacy - > Cognitive performance	-0.005	0.197	0.844	Insignificant
Teacher efficacy - > Teacher performance	0.113	3.623	0.000	Significant
Teacher innovation - > Cognitive performance	-0.052	1.627	0.104	Insignificant
Teacher innovation - > Teacher efficacy	0.570	16.210	0.000	Significant
Teacher innovation - > Teacher performance	0.558	16.123	0.000	Significant
Teacher performance - > Cognitive performance	0.026	0.878	0.380	Insignificant
Teacher competence - > Cognitive performance	0.019	0.613	0.540	Insignificant
Teacher competence - > Teacher efficacy	0.228	6.529	0.000	Significant
Teacher competence - > Teacher performance	0.304	8.297	0.000	Significant

TABLE 6 The influence of mediation.

	Original sample (O)	T statistics (|O/STDEV|)	*P* values	Information
Teacher innovation - > Teacher efficacy - > Cognitive performance	-0.005	0.305	0.761	Insignificant
Teacher competence - > Teacher performance - > Cognitive performance	0.007	0.865	0.387	Insignificant
Teacher competence - > Teacher efficacy - > Cognitive performance	-0.002	0.302	0.763	Insignificant
Teacher innovation - > Teacher efficacy - > Teacher performance - > Cognitive performance	0.002	0.821	0.412	Insignificant
Teacher innovation - > Teacher efficacy - > Teacher performance	0.064	3.477	0.001	Significant
Teacher competence - > Teacher efficacy - > Teacher performance	0.026	3.226	0.001	Significant
Teacher competence - > Teacher efficacy - > Teacher performance - > Cognitive performance	0.001	0.814	0.415	Insignificant
Teacher efficacy - > Teacher performance - > Cognitive performance	0.003	0.827	0.408	Insignificant
Teacher innovation - > Teacher performance - > Cognitive performance	0.013	0.871	0.384	Insignificant

TABLE 7 Effects of school climate moderation.

	Original sample (O)	*T* statistics (|O/STDEV|)	*P* values	Information
School climate x Teacher efficacy - > Cognitive achievement	0.026	1.105	0.269	Insignificant
School climate x Teacher innovation - > Cognitive achievement	-0.065	2.114	0.035	Significant
School climate x Teacher performance - > Cognitive achievement	0.012	0.443	0.658	Insignificant
School climate x Teacher competency - > Cognitive achievement	-0.012	0.481	0.630	Insignificant
School climate x Teacher efficacy - > Cognitive achievement	0.026	1.105	0.269	Insignificant

TABLE 8 R-Square Value.

	R-square	R-square adjusted
Cognitive performance	0.024	0.016
Teacher efficacy	0.576	0.575
Teacher performance	0.670	0.669

(Root Mean Square Error), and MAE (Mean Absolute Error). A Q^2 predict value greater than 0 on all variables indicates the model has predictive relevance. A positive Q^2 prediction confirms the predictive relevance of the model in PLS-SEM (Hair et al., 2017; Liengaard et al., 2021).

CVPAT is designed to compare two theoretically obtained models to determine their ability to simultaneously predict the indicators of all dependent latent variables. The results are evaluated based on the *p*-value of 0.05. If the *p*-value < 0.05, the model is significantly better than the random model, indicating strong predictive ability (Rigdon et al., 2017).

3.2 Student learning character model

Outer loading measure is a statistical measure used to see how far the indicator reflects the measurement of variables or the extent to which the indicator is valid. The prerequisite outer loading value of > 0.70 is considered significant (Hair et al., 2019), Cronbach's Alpha and

Composite Reliability values greater than 0.70 (Hair et al., 2017). It is described in the following Table 11.

3.2.1 Evaluation of the structure model (inner model)

3.2.2 Evaluate the merits and fit of the model

R-square is a measure that describes how much of the proportion of variance of dependent (endogenous) variables can be explained by independent (exogenous) variables in a model. In the analysis using Partial Least Squares-Structural Equation Modeling (PLS-SEM), the R-square value is the leading indicator in assessing the model's predictive power. The criteria for evaluating the R-square value consist of three main categories: a value of 0.75 or more is considered substantial, a value between 0.50 and less than 0.75 is considered moderate, and a value between 0.25 and less than 0.50 is considered weak. If the value is less than 0.25, the model's capabilities are considered weak (Musyaffi et al., 2022).

The PLSPredict evaluation table shows the results of testing the predictive ability of the PLS-SEM model using Q^2 predict, RMSE (Root Mean Square Error), and MAE (Mean Absolute Error). A Q^2 predict value greater than 0 on all variables indicates that the model has predictive relevance, and a positive Q^2 predict confirms the predictive relevance of the model in PLS-SEM (Liengaard et al., 2021; Hair et al., 2017; Shmueli et al., n.d.).

CVPAT is designed to compare two theoretically obtained models to determine their ability to simultaneously predict the indicators of all dependent latent variables. The results are evaluated based on the *p*-value of < 0.05, and then the model is significantly better than the random model, which indicates strong predictive ability (Rigdon et al., 2017).

TABLE 9 PLSPredict analysis data.

	Q^2predict	RMSE	MAE
Cognitive performance	-0.060	0.985	0.862
Teacher efficacy	0.574	0.654	0.477
Teacher performance	0.662	0.583	0.432

4 Discussion

4.1 Teacher learning character model on cognitive performance

The direct influence analysis shows that teacher competence significantly affects teacher efficacy and performance, but the direct influence on students' cognitive achievement is insignificant. In

TABLE 10 CVPAT test data.

	PLS loss	IA loss	Average loss difference	t value	p-value
Cognitive performance	0.234	0.235	-0.001	2.001	0.046
Teacher efficacy	0.489	0.935	-0.446	13.910	0.000
Teacher performance	0.668	1.047	-0.379	16.005	0.000
Overall	0.484	0.752	-0.268	17.020	0.000

TABLE 11 Outer loading, composite reliability, and average variance extracted.

Variable	Measurement items	Outer loading	Cronbachs alpha	Composite reliability	AVE
Learning iron	LB1	0.844	0.747	0.773	0.568
	LB4	0.724			
	LB5	0.730			
	LB8	0.710			
Learning concepts	KB5	0.870	0.717	0.722	0.779
	KB9	0.895			
Academic persistence	KA10	0.869	0.902	0.904	0.774
	KA2	0.870			
	KA3	0.918			
	KA6	0.861			
Cognitive achievement	HB24	0.727	0.604	0.605	0.558
	HB25	0.780			
	HB26	0.733			
School climate	IS1	0.866	0.751	0.798	0.660
	IS10	0.812			
	IS9	0.757			

contrast, teacher innovation significantly improves teacher efficacy and performance but does not directly contribute to student achievement. Teacher efficacy also significantly affects teacher performance but does not directly affect student achievement. These findings support the results of research that show that teacher characteristics, such as competence and innovation, have a more significant impact on the teaching process than direct student learning outcomes (Blömeke et al., 2022; Darling-Hammond et al., 2020). These results are also consistent with research conducted by König et al. (2021), which states that teacher competence increases confidence in learning management and that the direct impact on student learning outcomes is often insignificant. In addition, the direct effect of a teacher's character on learning outcomes is frequently influenced by mediating factors, such as teacher performance, student involvement, or the learning strategies used (Fackler and Malmberg, 2016; Wang et al., 2022).

School climate as a moderation variable in the relationship between the learning character of teachers and students' cognitive achievement. The results showed that school climate moderation significantly strengthened the relationship between teacher innovation and student cognitive achievement ($p < 0.05$). However, most of the other moderation relationships were insignificant, suggesting that the influence of school climate was limited to certain aspects of the teacher's learning character. Mediation analysis shows that teacher efficacy and performance play an important role in bridging the influence of teacher innovation on students' cognitive achievement. These findings are consistent with studies that show that a supportive and collaborative school environment can increase the effectiveness of teachers' innovation and efficacy in the learning process (Konstantinidou and Scherer, 2022; Wang and Degol, 2016). Other research also shows that a positive school climate can create a conducive learning atmosphere, thereby strengthening the effect of teachers' innovation and creativity on students' academic achievement (Berkowitz, 2022; Thapa et al., 2013). In addition, collaboration between teachers supported by a healthy school climate can increase collective efficacy and build a more effective learning culture (Collie et al., 2012; Fackler and Malmberg, 2016).

The R-square value showed that the model had moderate predictive abilities on efficacy (57.6%) and teacher performance (67%) but weak on students' cognitive achievement (2.4%). Evaluation of prediction capabilities via PLSPredict shows positive Q^2 predict values for most constructs, indicating the predictive relevance of the model (Hair et al., 2019). The results of the CVPAT show that this model is significantly better than the random model in predicting the indicator of the dependent latent variable with a $p < 0.05$. This is in line with previous research, which stated that PLS-SEM-based models are suitable for predicting complex relationships in the context of education (Shmueli et al., n.d.). In addition, the PLS-SEM model is often used to indicate relationships between latent variables in studies involving complex data, as this method can handle data imbalances and ensure prediction accuracy (Sarstedt et al., 2021). Other research also shows that PLSPredict provides reliable evaluation metrics, such as Q^2 predict, which are relevant in testing the predictive power of models (Memon et al., 2021). PLS-SEM has proven helpful in analyzing the complex relationship between school factors, teacher performance, and student learning outcomes (Ringle et al., 2020). In addition, this approach provides high flexibility in handling models with many latent indicators or variables (Rigdon et al., 2017).

4.2 Student learning character model on cognitive achievement

The results showed that students' learning character, which consisted of learning style, learning conception, and academic persistence, had a significant relationship with cognitive achievement directly and through mediation. Learning styles significantly affected cognitive achievement, with $p = 0.035$, suggesting that the way students process information had a significant impact on their learning outcomes. This is consistent with research showing that more effective learning styles, such as more in-depth information processing, can improve academic achievement (Alhadabi and Karpinski, 2020; Zimmerman, 2011). Although the concept of learning does not directly affect cognitive achievement, it significantly influences academic persistence, with $p = 0.000$, which becomes an indirect pathway to improve student achievement. Previous research has also confirmed that a better understanding of learning concepts can increase students' perseverance and motivation in learning (Furrer and Skinner, 2003; Schnitzler et al., 2021). In addition, academic persistence was found to be a key factor that directly and significantly affects cognitive achievement, which supports the findings of the study stating that perseverance in facing academic challenges has a significant influence on student learning outcomes (Duckworth and Quinn, 2009; Yeager et al., 2022).

Academic persistence mediated the relationship between learning conception and cognitive achievement with $p = 0.035$. Other mediation pathways, from learning through academic perseverance to cognitive achievement, are also significant. These findings support previous research highlighting the importance of academic perseverance as a determining factor in student learning success, especially in the face of academic challenges (Xu et al., 2023; Zepeda et al., 2020). Academic perseverance is essential in increasing students' perseverance to continue struggling under challenging conditions, contributing to better learning outcomes (Alhadabi and Karpinski, 2020; Duckworth, 2016; Kalia, 2021). This aligns with research showing that commitment is a stronger predictor of academic achievement than other factors, such as talent or intrinsic motivation (Yeager et al., 2022). The influence of school climate moderation in this relationship was largely insignificant, suggesting that internal factors influence students' learning character more than the external environment. While the school climate can support the learning process, internal factors include confidence and perseverance (Thapa and Cohen, 2023). Research results from Verner-Filion (2023) suggest that the role of school climate is more prominent in improving students' motivation and learning behavior than directly influencing academic achievement (Tables 12–17).

The evaluation of the goodness and compatibility of the model in this study showed varying results related to the ability to predict variables in the PLS-SEM model. The R-square value for the learning style variables (0.415) and academic persistence (0.595) indicates that the model has moderate predictive power. In contrast, the R-square value for students' cognitive achievement of only 0.026 suggests that other factors not covered by the model may also affect cognitive achievement, such as socio-economic factors or intrinsic motivation (Li et al., 2021). Further evaluation using PLSPredict showed that positive Q^2 predict values for learning style and academic persistence (0.413 and 0.489) confirmed the predictive relevance of the model. In contrast, negative Q^2 predict values for cognitive achievement (-0.053) showed that the model was less relevant in predicting students' cognitive achievement variance.

TABLE 12 Direct influence.

	Original sample (O)	*T* statistics (|O/STDEV|)	*P* values	Information
Learning style - > Cognitive achievement	-0.022	2.106	0.035	Significant
Conception of learning - > academic persistence	0.273	12.080	0.000	Significant
Conception of learning - > Concrete achievement	-0.021	1.097	0.273	Insignificant

TABLE 13 The influence of mediation.

	Original sample (O)	T statistics (|O/STDEV|)	P values	Information
Learning style - > academic persistence - > Cognitive achievement	-0.022	2.106	0.035	Significant
learning conception - > Learning style - > academic persistence	0.273	12.080	0.000	Significant
Conception of learning - > academic persistence - > Cognitive achievement	-0.022	2.109	0.035	Significant
Conception of learning - > Learning style - > Cognitive achievement	0.016	0.998	0.318	Insignificant
learning conception - > Learning style - > academic persistence - > Cognitive achievement	-0.014	2.094	0.036	Significant

TABLE 14 Data on the influence of school climate moderation.

	Original sample (O)	T statistics (|O/STDEV|)	P values	Information
School climate x Learning conception - > Concrete achievement	-0.025	1.063	0.288	Insignificant
school climate x learning style - > cognitive performance	0.007	0.371	0.711	Insignificant
School Climate x Academic persistence - > Congressional performance	-0.036	1.699	0.089	Insignificant

These findings are in line with previous research that indicates that the PLS-SEM model is very good at predicting variables related to students' internal characteristics but is limited in predicting external outcomes such as direct academic achievement (Liengaard et al., 2021; Shmueli et al., n.d.). The results of the CVPAT evaluation also confirmed that this model is significantly better than the random model in predicting latent variables with a p-value of < 0.05, confirming the predictive power of the model (Rigdon et al., 2017). Thus, it has proven effective in describing complex relationships in Education.

TABLE 15 *R*-square value.

	R-square	*R*-square adjusted
Learning style	0.415	0.415
Academic persistence	0.595	0.595
Cognitive performance	0.026	0.020

TABLE 16 PLSPredict analysis data.

	Q^2predict	RMSE	MAE
Learning style	0.413	0.768	0.598
Academic persistence	0.489	0.716	0.552
Cognitive performance	–0.053	0.983	0.861

4.3 Model comparison

Comparing the findings of the two models, there can be significant differences in how teachers' and students' learning characteristics affect cognitive achievement. The first model that tested the learning character of teachers showed that although teacher competence and innovation had a significant effect on teacher efficacy and performance, the direct influence on student achievement was not significant. This supports research that shows that teacher characteristics do influence the teaching process and teacher efficacy more, but their impact on student learning outcomes is often indirect or through mediating factors such as teacher performance and student involvement (Blömeke et al., 2022; Darling-Hammond et al., 2020). On the other hand, the second model that tests students' learning character shows that learning style, academic persistence, and learning conception have a significant direct or indirect influence on students' cognitive achievement. More effective learning styles, for example, are directly related to students' cognitive achievement, while academic persistence is a key factor that significantly affects achievement (Duckworth, 2016; Yeager et al., 2022).

Both models showed moderate predictive power for most constructs, but there were essential differences in their ability to predict students' cognitive achievement. The first model, which focuses on the teacher's learning character, showed higher R-square values for teacher efficacy and performance (0.576 and 0.67) but very low for student cognitive achievement (0.024), indicating that although teacher characteristics influence the learning process, other factors outside the model play a more significant role in student learning outcomes. In contrast, the second model that focuses on students' learning characters showed moderate R-square values for learning style and academic persistence (0.415 and 0.595) but low for cognitive achievement (0.026), which suggests that although students' internal factors have a significant influence on the learning process, this model cannot fully predict students' cognitive achievement, likely due to other external variables that are not accommodated. Evaluation using PLSPredict and

TABLE 17 CVPAT.

	PLS loss	IA loss	Average loss difference	*t* value	*p*-value
Learning style	0.847	1.111	−0.264	11.470	0.000
Academic persistence	0.814	1.312	−0.498	14.379	0.000
Cognitive performance	0.234	0.235	−0.001	2.299	0.022
Overall	0.668	0.945	−0.278	15.337	0.000

CVPAT showed that both models had good predictive abilities for latent variables, although they were limited in predicting cognitive achievement directly.

5 Conclusion

This study provides a comprehensive analysis of the factors that affect students' cognitive achievement by highlighting the role of teachers' learning characters and students' learning characters, which are moderated by the school climate. The results show that teacher innovation and efficacy significantly affect teacher performance, but their impact on students' cognitive achievement is limited. On the contrary, students' learning characteristics, such as learning style and academic persistence, show a more substantial influence directly or through mediation on students' cognitive achievement. In particular, academic persistence is an essential mediating variable in connecting learning conceptions and learning styles with academic outcomes.

School climate as a moderation variable has a selective role, significantly strengthening the relationship between teacher innovation and student cognitive achievement, although other moderation effects are largely insignificant. These findings confirm the complexity of the interaction between internal and external factors in the learning process, suggesting that teacher-focused interventions are more effective when supported by a conducive school environment.

Although the study was conducted in several schools with diverse characteristics, the results still have limitations in terms of generalization. The sample only included schools in North Maluku Province, so these findings may not be entirely applicable in areas with different education systems. In addition, the model does not include external factors such as educational policies, curriculum, and socio-economic backgrounds of students that can affect cognitive achievement. The model's ability to predict cognitive achievement is still limited, so further research with additional variables, such as socio-economic factors and students' intrinsic motivation, is needed. The PLS-Predict approach used emphasizes predictive rather than inferential aspects, so it has not been able to test causal relationships strongly. In addition, cross-sectional design limits the understanding of the dynamics of variable change. Therefore, further research is recommended to expand the scope of the sample, consider external variables, and explore strategies to improve teacher effectiveness and student engagement. These findings continue contributing to educational theory and practice and emphasize the importance of integrated strategies in creating supportive learning environments.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the participants or participants legal guardian/next of kin was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

SA: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. HS: Conceptualization, Supervision, Writing – review & editing. ER: Conceptualization, Supervision, Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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