Original Article

The effects of descriptive assessment on student learning and its relationship with mental health using structural equation modeling

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Abstract

Background: Student learning is influenced by numerous factors, with descriptive assessment being one of the key components. This study aims to analyze the effects of descriptive assessment on student learning and its relationship with mental health.

Methods: This descriptive-correlational study employed Structural Equation Modeling (SEM) using AMOS software to analyze the relationships among variables. The statistical population included elementary school students in Tehran during the academic year 2022-2023, from which were selected through simple random sampling. Inclusion and exclusion criteria were applied to ensure data validity, and participants reflected diverse socio-economic backgrounds. Standardized, validated questionnaires were used to measure descriptive assessment, learning outcomes, and mental health, with data collected under controlled classroom conditions.

Results: The results showed a significant relationship between attitudes toward hijab, health-promoting religious behaviors, and social health among female students. Also, descriptive assessment has a significant impact on student learning and mental health, leading to improvements in their understanding, learning outcomes, and mental well-being. Additionally, factors such as motivation, self-assessment, and received feedback play a crucial role in this process. The presented models indicated that descriptive assessment can indirectly improve academic performance and mental health by increasing motivation and enhancing self-assessment.

Conclusion: Descriptive assessment is recognized as an effective tool in the learning process and mental health of students. This study recommends that educational policymakers consider incorporating descriptive assessment as part of the educational evaluation system to improve student learning and mental health.

Keywords: Latent Class Analysis; Learning; Mental Health; Motivation; Self-Assessment; Students.

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Introduction

Descriptive assessment has been shown to positively influence students' academic performance and mental health by reducing anxiety, fostering intrinsic motivation, and promoting a deeper understanding of learning objectives. Learning is a complex and multidimensional process influenced by individual, social, cultural, and educational factors (1). A comprehensive understanding of this process requires examining the dynamic interaction among these factors. Among various evaluative approaches, descriptive assessment is considered one of the most effective methods for assessing students’ academic achievement and supporting their mental well-being (2). Unlike traditional assessment methods that primarily rely on numerical scores, descriptive assessment focuses on the learning process itself, identifying students’ strengths and weaknesses and offering constructive, goal-oriented feedback (3). When implemented appropriately, this approach can significantly enhance both the learning experience and students' psychological health. It enables educators to tailor instructional strategies to learners’ specific needs and encourages parents to engage more actively in supporting their children’s academic progress and emotional well-being. Moreover, psychological constructs such as motivation, self-confidence, and self-assessment skills are key mediators in the success of descriptive assessment, contributing further to its impact on mental health and academic performance (4).

The learning environment is also a key factor as it affects the success of descriptive assessment. Classrooms that use interactive approaches to assessment provide continuous feedback and help students better understand their learning process and mental health (5). Effective communication between school and family is another vital aspect of this type of assessment. In other words, providing parents with clear feedback can make them more involved in their children’s education and mental health support (6). Defining comprehensive criteria for measuring learning and mental health is one of the primary challenges in implementing descriptive assessment. Many assessments still rely on test results, while learning and mental health are continuous and dynamic processes. Thus, it is essential to include multiple criteria in assessing student performance to get a clearer picture of their progress and mental health (7).

Finally, empowering students to do self-assessment is a vital goal of descriptive assessment. This helps them to take responsibility for their own learning and mental health and to strengthen their critical thinking skills. Teachers are also involved in this process and should use appropriate methods to provide constructive feedback (8). The results of this study can help educational policymakers, teachers, and administrators improve educational processes and mental health and provide the conditions for increasing the quality of learning and mental health in schools.

Methodology

This study was an applied study regarding its purpose as its results can be used to improve the descriptive assessment process in primary schools and promote students' mental health.

This was also a descriptive-correlational study regarding methodology. It employed structural equation modeling (SEM) to examine the impact of descriptive assessment on improving students' learning and mental health. The study method was a combination of field studies and quantitative data analysis. This allowed the researcher to investigate the relationships between the study variables.

Research environment and population

The statistical population of this study consisted of all primary school students enrolled in public schools across various educational districts within Tehran during the 2022-2023 academic year. To enhance the generalizability of the findings, schools were randomly selected from different districts representing diverse socioeconomic and educational backgrounds. A cluster random sampling method was employed, enabling the inclusion of entire classes or groups of students from selected schools. The required sample size was determined using

Cochran’s formula, ensuring adequate statistical power for analysis. In addition to students, primary school teachers and administrators from the same institutions were included as complementary participants, allowing for a more comprehensive understanding of the impact of descriptive assessment from multiple perspectives.

Data collection tools

Standard questionnaires were used to collect research data. This questionnaire included two primary parts:

1. Descriptive assessment variable, measured using scientifically valid indicators.

2. Student learning improvement variable, which includes indicators such as academic achievement, understanding of concepts, learning motivation, and active participation in the classroom.

The content validity of the questionnaires was reviewed by a group of education and educational assessment experts and necessary modifications were applied. Cronbach's alpha coefficient was also used to measure the reliability of the data collection tool. Its value was calculated to be higher than 0.7, indicating the appropriate reliability of the questionnaires. The questionnaires were distributed electronically or in person among the participants. The data were recorded in the research database after collection.

The questionnaires were developed specifically for this study based on an extensive literature review of descriptive assessment and student learning constructs. To establish content validity, the questionnaires were evaluated by a panel of five experts in education and educational assessment, who provided feedback leading to necessary revisions. The reliability of the questionnaires was assessed through Cronbach’s alpha, with all scales achieving coefficients above 0.7, indicating acceptable internal consistency. Data were collected both electronically and in person.

Data analysis method

Structural equation modeling (SEM) was used to analyze the collected data. In this regard, the following steps were taken:

• Using descriptive statistics to examine the characteristics of the study population, including mean, standard deviation, frequency distribution, and descriptive graphs.

• Conducting confirmatory factor analysis (CFA) to examine the fitness of the measurement model and determine the degree of fit of the research indicators.

• Conducting path analysis to test the research hypotheses and examine the direct and indirect effects of variables on each other.

SPSS and AMOS software were used to perform these analyses. It has advanced capabilities for testing relationships between variables in the study model. Moreover, criteria such as the ratio of chi-squares to degrees of freedom (X^2/DF), comparative fit index (CFI), normalized fit index (NFI), and root mean square error of approximation (RMSEA) were used to assess the significance of the paths.

Ethical considerations

This study was conducted by observing ethical principles. All participants gave their informed consent to participate in the study after receiving complete information about the study goals. Respondents' information was kept confidential and the collected data were used only for research purposes. Moreover, the rights of the research subjects were respected at all stages of the study and any pressure or coercion to participate in the study was avoided.

Results

Based on Table 1, the majority of the participants had a PhD (9) and the rest had a Master’s degree (6), indicating their high

Table 1. Characteristics of the experts participating in the qualitative section of the study

Row	Degree	Job position	Educational level	Gender	Subject-related role	Age	History
1	Educational Management	University lecturer and researcher in related field	PhD	Male	Scientific	56	19
2	Educational Management	Manager	Master	Male	Scientific-Executive	45	15
3	Educational Management	Deputy	Master	Female	Scientific-Executive	40	12
4	Educational Management	Manager	Master	Male	Scientific-Executive	37	9
5	Government Management	University lecturer and researcher in related field	PhD	Male	Scientific	49	17
6	Educational Management	University lecturer and researcher in related field	PhD	Male	Scientific	49	19
7	Educational Management	Manager	Master	Male	Scientific-Executive	56	23
8	Educational Management	Manager	Master	Male	Scientific-Executive	40	15
9	Government Management	Manager	PhD	Male	Scientific	37	10
10	Expert	University lecturer and researcher	PhD	Male	Scientific	40	10
11	Expert	University lecturer and researcher	PhD	Female	Executive	44	13
12	Expert	manager	PhD	Male	Scientific	52	16
13	Expert	manager	Master	Male	Executive	48	11
14	Expert	University lecturer and manager	PhD	Male	Scientific	36	8
15	Expert	University lecturer and manager	PhD	Male	Executive	51	20

education level. Regarding their job position, 6 were university lecturers, 6 were managers, 2 were deputies, and 1 was an executive expert, providing a combination of academic and executive perspectives. Regarding the gender, they were mostly male (12 males and 3 females). The age of the participants varied between 36 and 56 years, and most of them were in the 40-50 age range. Their employment history ranged from 8 to 23 years, which is more than 10 years of history. These characteristics increased the academic and executive credibility of the research and made the proposed model more applicable.

Cronbach's alpha and composite reliability were used to calculate the possibility of replicability and the possibility of generalizing the results to other samples.

The results of Cronbach's alpha and composite reliability coefficients in Table 2 showed that the values of these indices for all latent variables were higher than 0.7. Thus, the reliability of the measurement tools using these two indices was confirmed. The average variance extracted (AVE) is one of the important indices for examining the convergent validity in measurement models. It indicates how much of the variance of a construct is explained by its observed indices. Based on the criterion proposed by Fornell & Larcker, the AVE value must be at least 0.50 or more to confirm convergent validity

Table 2. Cronbach's alpha and composite reliability

Variables	Cronbach's alpha	composite reliability
Causal conditions	0.859	0.855
Core phenomenon	0.850	0.863
Strategies	0.851	0.866
Outcomes	0.760	0.815
Inhibitors	0.872	0.877
Drivers	0.898	0.874
Contextual factors	0.855	0.823

. In Table 3, all variables have AVE values higher than 0.50, indicating the confirmation of convergent validity for all model dimensions. The highest AVE values are related to the causal conditions dimension (0.693) and the core phenomenon (0.691), indicating that these dimensions have the highest level of explained variance. In contrast, the strategies dimension (0.513) has the lowest AVE value. Although it is above the threshold of 0.50, it has less explained variance than other variables.

The results show that all model dimensions have acceptable convergent validity. The AVE value in all variables is above the threshold of 0.50. The causal conditions and core phenomenon variables have the highest level of explained variance, indicating the high importance of these factors in the model. In contrast, the strategies dimension has the lowest AVE value, which may indicate the need to revise some of its items to increase the explained variance. Other dimensions, including outcomes, inhibitors, drivers, and contextual factors are also within the acceptable range, indicating the appropriate validity of the model regarding convergent validity. The average variance extracted (AVE) was calculated for different dimensions to examine the convergent validity in this study. These values indicate the degree of convergence between the indicators and different dimensions of the model. The different dimensions have different AVEs as follows:

Causal conditions with an AVE of 0.693 indicates the highest level of convergent validity.

Primary phenomena with an AVE 0.691 indicate a good level of convergent validity.

Strategies with an AVE of 0.513 have the lowest value among the different dimensions and may need further investigation and improvement.

Outcomes with an AVE of 0.609 indicate a desirable level of convergent validity.

Inhibitors with an AVE of 0.653 indicate acceptable convergent validity.

Drivers with an AVE of 0.579 are at a moderate level.

The contextual factors with an AVE of 0.582 indicate a good level of convergent validity.

The results of testing the Heterotrait-Monotrait (HTMT) validity show that all values are less than the threshold of 0.85, confirming the appropriate divergent validity among the model variables. The HTMT value between causal conditions and the core phenomenon (0.381) and between strategies and the core phenomenon (0.376) is relatively low, indicating that these variables are well differentiated from each other. The highest HTMT value is related to the relationship between the drivers and strategies (0.653) and the contextual factors and the core phenomenon (0.689), but it is still within the acceptable range and indicates an appropriate distinction between these constructs. Generally, the obtained values indicate that the different dimensions of the model have conceptual distinction, and the independent variables are well separated from each other, confirming the validity of the model's divergent validity Table 3.

Table 3. Univariate-dual divergent validity of HTMT

Row	Causal conditions	Core phenomenon	Strategies	Outcomes	Inhibitors	Drivers	Contextual factors
Causal conditions	-						
Core phenomenon	0.381	-					
Strategies	0.335	0.376	-				
Outcomes	0.549	0.497	0.287	-			
Inhibitors	0.282	0.417	0.609	0.446	-		
Drivers	0.508	0.601	0.653	0.502	0.513	-	
Contextual factors	0.562	0.689	0.318	0.609	0.288	0.425	-

Structural model tests

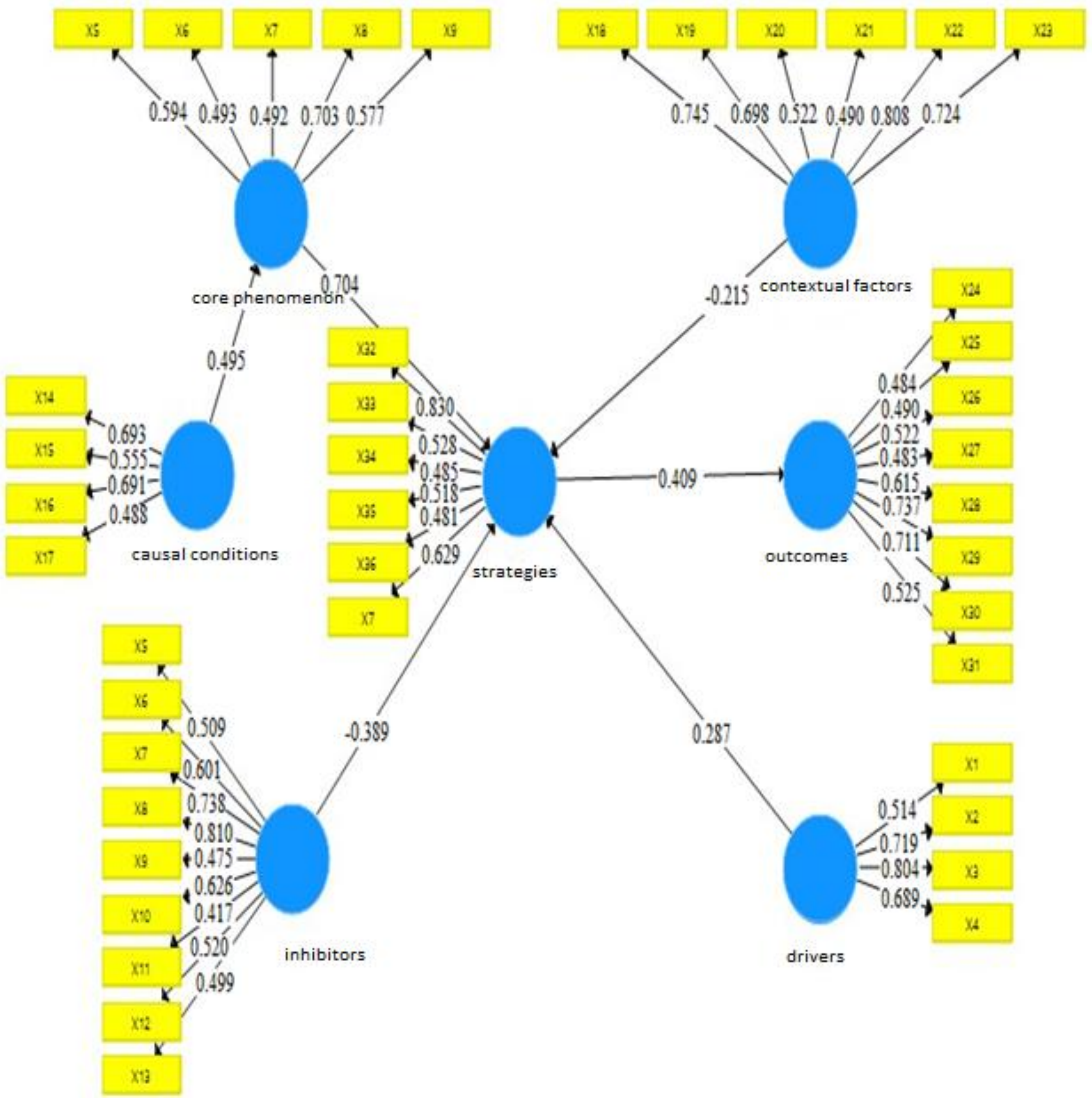

Figure 1. Path coefficient diagram

Figure 1 illustrates the path coefficients. The range of this coefficient is between -1 and 1. The higher the coefficient is, the stronger the direct and strong relationship between the explanatory and dependent variables is, and the higher the coefficient is, the inverse relationship between the explanatory and dependent variables is. The explanatory power of the dependent variable increases if the relationship between the research variables is strong. Analysis of Table 4 shows that the coefficient of determination (r^2) of the strategies variable with a value of 0.848 and the outcomes with a value of 0.833 have the highest coefficient of determination, indicating the high power of the model in predicting these variables based on the independent variables. These values indicate that 84.8% of the changes in strategies and 83.3% of the changes in outcomes are explained by the model variables, indicating the high predictive power of the model in these areas. In contrast, the core phenomenon variable has a lower coefficient of determination

(0.223), indicating that the independent variables in the model explain only 22.3% of its variation. The adjusted coefficient of determination also changes slightly, confirming that the model still has good predictive power for strategies and outcomes even when considering the number of predictor variables. These results generally indicate that the model performs r well in explaining the key variables, but that more explanatory variables could be included in the model to improve the prediction of the core phenomenon.

Table 4. Coefficient of Determination

Indicator	Coefficient of Determination	Adjusted coefficient of determination
Strategies	0.848	0.844
outcomes	0.833	0.825
Core phenomenon	0.233	0.219

Analysis of Table 5 of the prediction coefficient q^2 indicates that all variables in the model have positive values in the range of 0 to 1, indicating the appropriate predictive power of the model. The q^2 value for the core phenomenon variable (0.847) has the highest value, indicating that the model has a high power in predicting this variable. The variables of inhibitors (0.704) and strategies (0.681) also have high values, indicating the good accuracy of the model in predicting these variables. Causal conditions (0.584), drivers (0.607), and contextual factors (0.524) also have appropriate values, confirming the medium to high predictability of the model in these parts. The lowest q^2 value is related to outcomes (0.528), indicating that the prediction of this variable in the model is less accurate than other variables, but still falls within an acceptable range. These results generally indicate that the model has good predictive ability and performs particularly well on the core phenomenon, strategies, and inhibitors, but the prediction accuracy of some dimensions can be improved by reexamining the predictor variables.

Table 5. Coefficient of Determination q2

Dimensions	**q2** Statistic
Causal conditions	0.584
Core phenomenon	0.847
Strategies	0.681
outcomes	0.528
Inhibitors	0.704
Drivers	0.607
Contextual factors	0.524

Path Analysis Coefficients

Figure 2 illustrates the significance of the coefficients in the path analysis test. The t-statistic is used to calculate the significance test. The relationship between the inhibitors and strategies is significant at the 95% confidence level. The value of this statistic is 6.029 (p-value ≤ 0.05).

Overall fit of structural equation model

The model fit index in the PLS approach is known as the GOF index. In these models, r2 alone cannot examine the goodness of fit of the model, as in regression models. The calculation of this index is as follows.

$$\text{GOF} = \sqrt{= \text{avrage(communality)}^\wedge 2 * r^\wedge 2}$$

These values are 0.1, 0.25, and 0.36. A value of 0.1 indicates weak, 0.25 indicates moderate, and 0.36 indicates strong relationships in the estimated model. The results of the overall model fit indicate that the model has appropriate indices. Strategies (0.844) and outcomes (0.825) have high coefficients of determination, indicating the high explanatory power of the model, but the core phenomenon (0.219) has a low value and needs further examination. The shared values also indicate that the outcomes (0.834) and strategies (0.786) are well explained, while the core phenomenon (0.359) should be revised. The overall GOF index with a value of 0.711 indicates a strong fit for the model. The model has good validity, but influential variables can be revised to improve the explanation of the core phenomenon Table 6.

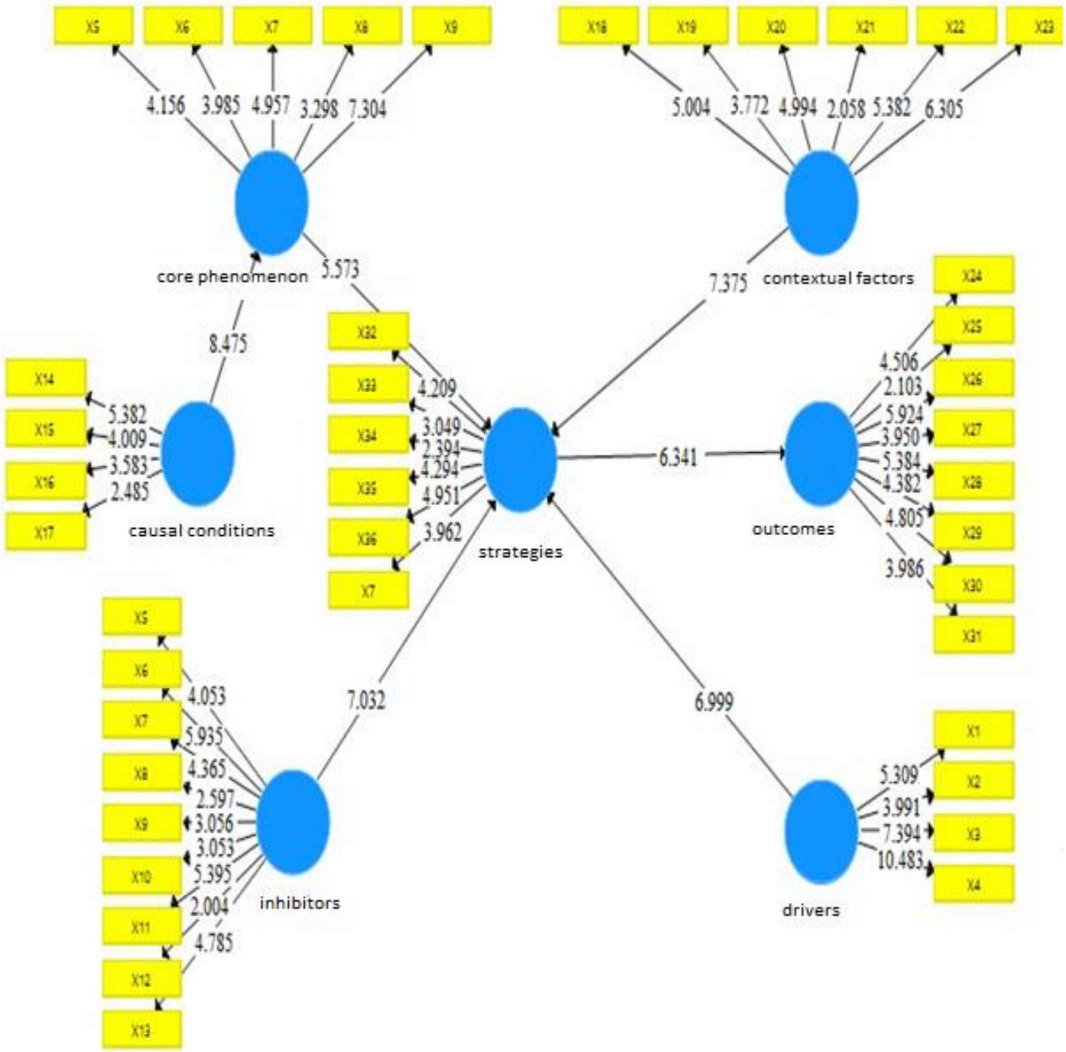

Figure 2. Significance of path coefficients

Table 6. Overall model fit results

Variables	Coefficient of the determination	shared values	GOF
Strategies	0.844	0.786	
Outcomes	0.825	0.834	0.711
Core phenomenon	0.219	0.359	

Discussion

The results of this study provide robust evidence for the reliability, validity, and overall predictive power of the proposed model. The internal consistency of the measurement constructs, as assessed through Cronbach's alpha and composite reliability coefficients, exceeded the acceptable threshold of 0.70 for all dimensions. These findings indicate that the measurement instruments used in this research are both stable and replicable, thus ensuring generalisability across other populations or contexts.

In terms of convergent validity, the Average Variance Extracted (AVE) for all constructs was above 0.50, meeting the standard recommended by Fornell and Larcker. Notably, the highest AVE values were observed in the constructs of causal conditions (0.693) and core phenomenon (0.691), highlighting their strong measurement quality and significant contribution to the overall explanatory framework. The strategies construct, while still above the threshold (0.513), exhibited the lowest AVE, suggesting a potential need to revisit or refine some of its measurement items to enhance its explanatory power.

The discriminant validity of the model was also confirmed through the HTMT criterion, with all HTMT values remaining below the 0.85 threshold. This indicates that each construct maintains sufficient conceptual independence from the others. The relatively low HTMT values between core constructs—such as causal conditions and the core phenomenon (0.381), and strategies and the core phenomenon (0.376)—further reinforce the theoretical distinctiveness of these variables. While the highest HTMT values were observed between drivers and strategies (0.653), and between contextual factors and the core phenomenon (0.689), they still remain within the acceptable range, confirming a valid construct separation

Improving the quality of students' learning and promoting their mental health is one of the most crucial concerns of educational policymakers and researchers in modern educational systems. In this regard, assessment methods are one of the vital factors affecting the learning process and mental health. Descriptive assessment is one of the alternative methods for measuring academic achievement and improving mental health. It has been considered a new approach in recent years to improve the quality of learning and mental health of students. Descriptive assessment emphasizes qualitative feedback, encouraging critical thinking, self-regulation, and student involvement in the learning process, and improving mental health instead of focusing merely on numerical scores.

The present study examined the impact of descriptive assessment on enhancing students' learning and mental health using structural equation modeling (SEM). This advanced statistical approach enabled the identification and analysis of the relationships between key variables influencing learning and mental well-being, and facilitated the evaluation of both direct and indirect effects of descriptive assessment. By employing sophisticated modeling techniques, the study explored how descriptive assessment contributes to academic achievement and mental health through mediating variables such as learning strategies, self-regulation, and academic motivation.

The findings from the data analysis demonstrated that the measurement instrument utilised in this research possessed acceptable levels of reliability. Specifically, Cronbach's alpha and composite reliability values for all latent variables exceeded the threshold of 0.7, thereby affirming the internal consistency and reliability of the research tool. Reliability is a fundamental criterion in quantitative research, ensuring both the reproducibility and generalisability of the findings (9). These results align with prior studies which suggest that high Cronbach's alpha coefficients indicate strong internal consistency of the measurement constructs (10).

In terms of convergent validity, the Average Variance Extracted (AVE) values for all constructs were above 0.50, consistent with the benchmark proposed by Fornell and Larcker. This indicates that the constructs account for a satisfactory proportion of variance in their respective observed indicators (10). Among these constructs, the causal conditions and the core phenomenon exhibited the highest AVE values, highlighting their significant influence within the research model. Conversely, the strategies variable yielded the lowest AVE value, suggesting that some of its indicators may require refinement to enhance explanatory adequacy. This observation is in line with the findings of Vargas-Mendoza & Gallardo, who emphasised the importance of active learning strategies and academic motivation as critical contributors to academic performance (11).

Further evaluation of discriminant validity revealed that all inter-construct correlations were below 0.85, thereby confirming adequate conceptual distinction among the model's constructs, in accordance with established validation criteria (12). Notably, the Heterotrait-Monotrait (HTMT) ratio between the causal conditions and the core phenomenon was the lowest, signifying a high degree of differentiation between these dimensions. This result corroborates findings from previous research indicating that strong discriminant validity enhances the credibility and theoretical precision of structural models (13).

The results of the path analysis and coefficient of determination (R^2) indicated that the strategies variable ($R^2 = 0.848$) and outcomes variable ($R^2 = 0.833$) had the highest explanatory power within the model. These findings suggest that the independent variables within the model effectively accounted for the observed variance in these constructs. In contrast, the core phenomenon exhibited a lower R^2 value (0.223), implying that additional unexamined factors may influence this variable and should be investigated in future research. This result supports the study by Brown et al., who highlighted the role of descriptive assessment in promoting academic self-regulation and alleviating test anxiety by offering qualitative feedback (14).

Additionally, the q^2 statistic was positive for all constructs, indicating the model's adequate predictive relevance. The core phenomenon displayed the highest q^2 value (0.847), followed by inhibitors (0.704) and strategies (0.681), confirming that the model exhibits strong predictive accuracy. These findings suggest that the constructs included in the model possess significant capacity to predict changes in the dependent variables. The Goodness of Fit (GOF) index was calculated at 0.711, signifying a strong overall model fit. Model fit is a critical indicator in SEM, reflecting the extent to which the proposed theoretical framework aligns with the empirical data. The results affirm that the model has a robust structural configuration and that the hypothesised paths among the constructs are well-supported by the data.

Conclusion

The study results revealed that descriptive assessment improves student learning and this effect is explained through mediating variables such as learning strategies, self-regulation, and academic motivation. The reliability and validity of the measurement tools used in this study were confirmed and the conceptual model of the research showed a good fit. The results of the path analysis revealed that the variables of learning strategies and educational outcomes had the highest level of effect, while some variables, such as the core phenomenon, require further investigation to identify other effective factors. Practically, this study emphasizes the need to review educational assessment methods and suggests that educational policymakers combine traditional assessment methods with modern approaches to improve the quality of learning. Additionally, teachers are recommended to pay more attention to strengthening students' self-regulation and learning strategies in the assessment process. Finally, it is recommended that future studies investigate the effect of descriptive assessment at different educational levels and consider the role of other effective variables such as personality traits, learning environment, and parental support in similar conceptual models.

Limitations

This study, like any other study, suffers from some limitations. One of the major limitations is the use of cross-sectional data, limiting the capability to examine changes over time. Moreover, the measurement tools were developed within a specific framework and may need to be adapted to other settings or cultures. Thus, it is recommended that future studies also use qualitative methods to complement the quantitative results.

Authors' contribution

Jameleh Farhudi and Vali Mehdinezhad developed the study concept and design. Mahnoosh Abedini and Jameleh Farhudi acquired the data. Jameleh Farhudi and Vali Mehdinezhad analyzed and interpreted the data, and wrote the first draft of the manuscript. All authors contributed to the intellectual content, manuscript editing and read and approved the final manuscript.

Informed consent

Questionnaires were filled with the participants' satisfaction and written consent was obtained from the participants in this study.

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Conflict of interest

The authors declare that they have no conflict of interests.

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