Attitudes Toward Statistics as Predictors of Learning Strategy in Statistics Education: A Logistic Regression Analysis

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ABSTRACT

Statistics is a core competency in higher education; however, many undergraduates approach introductory statistics courses with anxiety, low confidence, and perceptions of difficulty that may influence their learning strategies. This study investigated whether multidimensional attitudes toward statistics predicted undergraduate students' adoption of deep rather than surface learning strategies. A quantitative cross-sectional study was conducted among 306 undergraduates enrolled in introductory statistics courses at a Malaysian public university. Data were collected using adapted versions of the Survey of Attitudes Toward Statistics (SATS-36) and the Revised Two-Factor Study Process Questionnaire (R-SPQ-2F). Binary logistic regression was employed to estimate the probability of adopting a deep learning strategy based on six attitudinal dimensions: affect, cognitive competence, value, perceived difficulty, interest, and effort. The findings indicated that effort was the strongest positive predictor of deep learning strategy adoption (OR = 2.475, 95% CI [1.511, 4.051]), followed by interest (OR = 1.871, 95% CI [1.132, 3.093]). Conversely, perceived difficulty was negatively associated with the adoption of a deep learning strategy (OR = 0.493, 95% CI [0.258, 0.942]), indicating that students who perceived statistics as more difficult were less likely to adopt a deep learning strategy. The model achieved an overall classification accuracy of 67.0% and demonstrated greater accuracy in identifying deep learners than surface learners. These findings highlight the importance of strengthening students' effort and interest while reducing perceived difficulty to promote deeper engagement with statistical learning in higher education.

Keywords: Binary logistic regression; Deep learning; Learning strategies; SATS-36; Statistics attitude; Surface learning

INTRODUCTION

Statistics is a foundational discipline across scientific and professional fields because it supports systematic data collection, synthesis, and inferential reasoning [1]. In response to the growing demand for data-informed competencies, higher education institutions worldwide, including those in Malaysia, have incorporated introductory statistics as a compulsory subject across a wide range of undergraduate programmes [2]. Despite its relevance, however, many students continue to perceive statistics as difficult, anxiety-inducing, and disconnected from their disciplinary interests [1], [3]. Such perceptions may influence how students allocate effort, tolerate uncertainty, and respond to cognitively demanding statistics learning tasks [4].

Within educational psychology, attitudes toward statistics are understood as a multidimensional construct encompassing students' beliefs, emotions, and behavioural tendencies toward the subject, which may shape their engagement with statistics learning activities [5]. Developing positive attitudes toward statistics is important because such attitudes are associated with deeper conceptual understanding, greater persistence, and more effective application of statistical knowledge [6], [7]. Accordingly, assessing students' attitudes toward statistics is essential because these attitudes may influence their motivation to internalise statistical concepts and apply them meaningfully in real-world contexts [8]. In contrast, negative attitudes and heightened anxiety may encourage students to rely on superficial learning strategies, such as rote memorisation, rather than developing a meaningful conceptual understanding of the subject.

Educational psychology further suggests that students' attitudes may influence the learning strategies they adopt [6], [7]. Learning strategies are commonly classified as either deep or surface strategies [9]. A deep learning strategy is characterised by an intention to understand meaning, integrate new concepts with prior knowledge, and apply ideas critically [10], [11]. In contrast, a surface learning strategy is associated with memorisation, routine reproduction, and task completion with minimal conceptual engagement [12]. The adoption of these learning strategies may be influenced by students' perceptions and motivational orientations. Students who value statistics, recognise its relevance, and persist despite experiencing difficulty may be more likely to adopt deep learning strategies. Conversely, students who perceive statistics as threatening or excessively difficult may rely on surface learning strategies as a means of coping with assessment demands [13].

Although previous studies have examined students' attitudes toward statistics and their academic performance [14], comparatively limited attention has been given to the extent to which multidimensional attitudes toward statistics predict students' learning strategy choices, particularly within Malaysian public universities. To address this gap, the present study examines how different dimensions of students' attitudes toward statistics predict their probability of adopting deep rather than surface learning strategies using binary logistic regression. Specifically, the study addresses the following research questions: (1) Which dimensions of attitudes toward statistics significantly predict students' learning strategies after controlling for the other attitudinal dimensions? (2) What are the direction and magnitude of the effects of the significant predictors? and (3) How accurately does the logistic regression model classify students as adopting deep or surface learning strategies? The findings are expected to provide empirical evidence that can inform instructional planning, curriculum enhancement, and targeted academic support in statistics education.

METHODS AND MATERIALS

Research Design

This study employed a quantitative, cross-sectional, predictive research design. Binary logistic regression was selected because the dependent variable was dichotomous, with learning strategy coded as 1 for a deep learning strategy and 0 for a surface learning strategy. Binary logistic regression is appropriate for estimating the probability of an outcome comprising two categories based on a set of predictor variables [15].

Participants

The target population comprised undergraduate students enrolled in introductory statistics courses at Universiti Teknologi MARA (UiTM), Malaysia. Eligible participants were diploma- or bachelor's-degree students who had acquired at least a basic understanding of statistics at the time of data collection. Participants were recruited from undergraduate courses that covered introductory statistics. Convenience sampling was employed, resulting in a final sample of 306 respondents.

Ethical approval was obtained from the university's research ethics committee before data collection commenced (Approval Code: REC/1655/2025). The questionnaire was administered online through Google Forms. Before completing the survey, participants provided informed consent and were informed that their participation was voluntary and that their responses would remain anonymous and confidential.

Research Instruments

Data were collected using a self-administered structured questionnaire adapted from previously validated instruments. The questionnaire comprised two main sections.

Section A: Survey of Attitudes Towards Statistics

The Survey of Attitudes Toward Statistics (SATS-36), adapted from Schau [16], was used to assess students' attitudes toward statistics across six dimensions. Responses were recorded using a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). The six dimensions were defined as follows:

- **Affect**: students' positive or negative emotional responses toward statistics;
- **Cognitive Competence**: students' self-perceptions of their intellectual ability to understand and perform statistical tasks;
- **Value**: students' perceptions of the relevance and usefulness of statistics in academic, personal, and professional contexts;
- **Perceived Difficulty**: students' perceptions of statistics as a difficult subject;
- **Interest**: students' curiosity about and engagement with statistics; and
- **Effort**: the amount of active work students invests in learning statistics.

Section B: Revised Two-Factor Study Process Questionnaire (R-SPQ-2F)

The Revised Two-Factor Study Process Questionnaire (R-SPQ-2F), adapted from Biggs et al. [17], was used to assess deep and surface learning approaches within the context of statistics education. The instrument comprised 20 items

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representing deep and surface motives and strategies. Each item was rated on a five-point Likert scale ranging from 1 (*only rarely true of me*) to 5 (*always true of me*). The item scores were aggregated and subsequently categorised using a median-split procedure to construct the dichotomous dependent variable. Respondents classified as adopting a deep learning strategy were coded as 1, whereas those classified as adopting a surface learning strategy were coded as 0. To improve item clarity and reduce potential respondent confusion, negatively worded items were rephrased positively before the questionnaire was administered.

A pilot study involving 30 respondents was conducted to assess the internal consistency of the adapted SATS-36 and R-SPQ-2F constructs. The results indicated acceptable to excellent reliability, with Cronbach's alpha coefficients ranging from 0.794 to 0.921, as presented in Table 1 [18].

Table 1: Psychometric Properties of the Adapted SATS-36 and R-SPQ-2F Constructs

Construct	**Instrument Section**	**Number of Items**	**Cronbach's alpha[a]**	**Interpretation**
Affect	SATS-36	6	0.794	Acceptable Internal Consistency
Cognitive Competence	SATS-36	6	0.798	Acceptable Internal Consistency
Value	SATS-36	9	0.921	Excellent Internal Consistency
Perceived Difficulty	SATS-36	7	0.878	Good Internal Consistency
Interest	SATS-36	4	0.840	Good Internal Consistency
Effort	SATS-36	4	0.869	Good Internal Consistency
Deep Learning Strategy	R-SPQ-2F	10	0.875	Good Internal Consistency
Surface Learning Strategy	R-SPQ-2F	10	0.867	Good Internal Consistency

Note. Cronbach's alpha (α) coefficients were interpreted as follows: 0.70–0.79 = acceptable internal consistency; 0.80–0.89 = good internal consistency; and ≥ 0.90 = excellent internal consistency [18].

Conceptual Framework of the study

The conceptual framework proposes that six dimensions of attitudes toward statistics—affect, cognitive competence, value, perceived difficulty, interest, and effort—predict students' adoption of deep or surface learning strategies. The proposed relationships are illustrated in Figure 1.

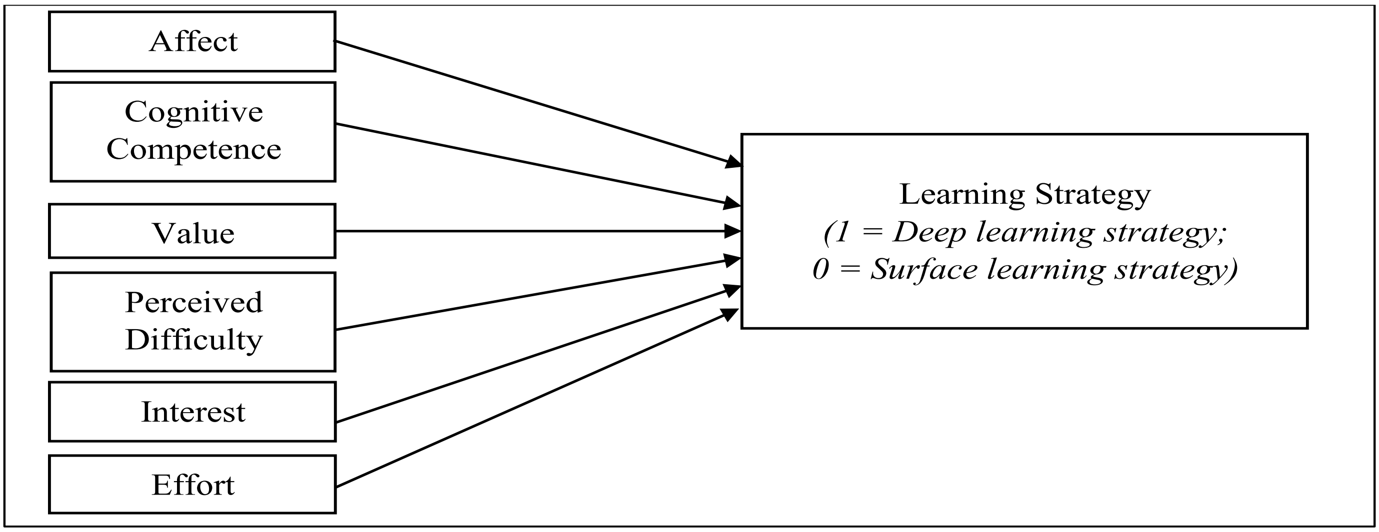

Figure 1. Conceptual Framework of Attitudinal Dimensions Predicting Students' Learning Strategies

In the proposed framework, the six dimensions of attitudes toward statistics serve as the independent variables, whereas students' learning strategy is the dependent variable. The dependent variable is dichotomised into deep learning strategy, coded as 1, and surface learning strategy, coded as 0. The directional arrows represent the hypothesised predictive relationships between each attitudinal dimension and students' learning strategy.

Data Analysis and Model Specification

Statistical analysis was conducted using IBM SPSS Version 26.0. Descriptive statistics were used to summarize participant characteristics and scale scores. Binary logistic regression was then used to estimate the probability of deep learning strategy adoption from the six attitude dimensions. The dependent variable (learning strategy) was dichotomized by binary classification (1 = deep learning, 0 = surface learning). The model can be expressed as:

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 Affect_i + \beta_2 Cognitive\ Competence_i + \beta_3 Value_i + \beta_4 Perceived\ Difficulty_i + \beta_5 Interest_i + \beta_6 Effort_i$$

Where,

p_i represents the probability that student i adopts a deep learning strategy ($Y_i = 1$);

$1 - p_i$represents the probability that student i adopts a surface learning strategy ($Y_i = 0$);

β_0 is the intercept; and

$\beta_1 - \beta_6$ are the regression coefficients corresponding to the six attitudinal dimensions. Each coefficient represents the change in the log-odds of adopting a deep learning strategy associated with a one-unit increase in the respective predictor, while holding the other predictors constant. The exponentiated coefficient, $\exp(\beta_j)$, represents the odds ratio associated with predictor j.

Backward elimination was used to derive a parsimonious model, with predictors retained at a significance level of $p < 0.05$. Adjusted odds ratios (ORs) and their 95% confidence intervals (CIs) were reported to indicate the direction and magnitude of the associations. Overall model significance was assessed using the omnibus likelihood-ratio test, while model explanatory power was evaluated using Nagelkerke's R^2. Model calibration was examined using the Hosmer–Lemeshow goodness-of-fit test. Predictive performance was assessed using overall classification accuracy, sensitivity, specificity, balanced accuracy, and the area under the receiver operating characteristic curve (ROC–AUC). Sensitivity represented the proportion of deep learners correctly classified, whereas specificity represented the proportion of surface learners correctly classified. Multicollinearity among the predictors was evaluated using tolerance and variance inflation factor values. The linearity of continuous predictors in the logit was assessed using the Box–Tidwell procedure, and influential observations were examined using standardised residuals, leverage values, and Cook's distance.

RESULTS

Model Fit and Diagnostics

The final binary logistic regression model retained three statistically significant predictors: effort, interest, and perceived difficulty. The model was statistically significant, χ^2 (3) = 106.110, p < 0.001, and explained a moderate proportion of the variation in learning strategy classification (as shown in Table 2). The model's classification accuracy, sensitivity, specificity, and balanced accuracy are presented in Table 2.

Table 2: Model-Fit and Diagnostic Statistics for the Final Three-Predictor Logistic Regression Model

Diagnostic	Result to report	Interpretation
Retained predictors	Effort, interest, and perceived difficulty	Three predictors remained after backward elimination.
Omnibus likelihood-ratio test	χ^2 (3) = 106.110, p < 0.001	The final model fitted the data significantly better than the intercept-only model.
Nagelkerke R-squared	0.412	The final model demonstrated moderate explanatory power.
Hosmer-Lemeshow test	χ^2 (8) = 7.140, p = 0.521	No statistically significant evidence of inadequate model fit was detected.
Events per variable	122 surface cases ÷ 3 predictors = 40.7	The sample size was adequate for estimating the final model.
Multicollinearity	VIF range = 1.250-3.919; Tolerance = 0.255-0.800	No serious multicollinearity among the three retained predictors.
Linearity in the logit	Box-Tidwell p-value range = 0.06-0.542	No statistically significant violation of linearity in the logit was detected.

Influential and unusual cases	Max Cook's Distance = 0.018; Leverage = 0.045; Standardized Residual Residuals = −2.61 to 2.74	No case was excessively influential, although unusual residuals should be examined.
Discrimination	ROC-AUC = 0.717, 95% CI [0.657, 0.777]	Indicates the model's ability to distinguish between deep and surface learners.

The nonsignificant Hosmer–Lemeshow test indicated adequate model fit, while the events-per-variable ratio of 40.7 supported sample-size adequacy. Diagnostic results revealed no serious multicollinearity, no violation of the linearity-in-the-logit assumption, and no excessively influential observations. The model also demonstrated acceptable discriminatory ability in distinguishing between deep and surface learners, with an ROC–AUC of 0.717, 95% CI [0.657, 0.777]. Overall, the findings indicate that the final model was statistically robust and adequately fitted for predicting students' learning strategies.

Logistic Regression Model Estimation

The final binary logistic regression model identified interest, effort, and perceived difficulty as statistically significant predictors of deep learning strategy adoption (see Table 3).

Table 3: Final Binary Logistic Regression Model Predicting Deep Learning Strategy Adoption

Predictor	B	SE	Wald χ^2	p-value	Adjusted OR Exp(B)	95% CI for Exp(B)
Interest	0.626	0.256	5.973	0.015*	1.871	[1.132, 3.093]
Effort	0.906	0.252	12.967	< 0.001*	2.475	[1.511, 4.051]
Perceived Difficulty	-0.707	0.330	4.592	0.032*	0.493	[0.258, 0.942]
Constant	-6.976	1.983	12.369	< 0.001	0.001	-

Note. Reference category: surface learning strategy (0); target category = deep learning strategy (1). *Significant at $p < 0.05$. OR = odds ratio; CI = confidence interval; OR > 1 indicates higher likelihood of deep learning; OR < 1 indicates surface learning.

Among these three predictors, effort was the strongest positive predictor of deep learning strategy adoption (B = 0.906, SE = 0.252, Wald χ^2 = 12.967, $p < 0.001$). Holding interest and perceived difficulty constant, each one-unit increase in students' effort toward learning statistics was associated with 2.475 times higher odds of adopting a deep rather than a surface learning strategy (OR = 2.475, 95% CI [1.511, 4.051]). This corresponds to a 147.5% increase in the odds of adopting a deep learning strategy.

Interest was also positively associated with deep learning strategy adoption, (B = 0.626, SE = 0.256, Wald χ^2 = 5.973, p = 0.015). Holding effort and perceived difficulty constant, each one-unit increase in students' interest in statistics was associated with 87.1% higher odds of adopting a deep rather than a surface learning strategy (OR = 1.871, 95% CI [1.132, 3.093]).

In contrast, perceived difficulty was negatively associated with deep learning strategy adoption (B = - 0.707, SE = 0.330, Wald χ^2 = 4.592, p = 0.032). A one-unit increase in perceived difficulty was associated with a 50.7% reduction in the odds of adopting a deep learning strategy, holding interest and effort constant (OR = 0.493, 95% CI [0.258, 0.942]). Thus, students who perceived statistics as more difficult were less likely to adopt a deep learning strategy. Cognitive competence, value, and affect were not statistically significant predictors (p -value > 0.05). The final predictive model equation was:

$$\ln\left(\frac{p}{1-p}\right) = -6.976 + 0.626(\text{Interest}) + 0.906(\text{Effort}) - 0.707(\text{Perceived Difficulty})$$

The positive coefficients for interest and effort indicate higher log odds of adopting a deep learning strategy, whereas the negative coefficient for perceived difficulty indicates lower log odds of adopting a deep learning strategy.

Classification Performance

As shown in Table 4, using a classification cut-off of 0.50, the model correctly identified 152 of the 184 students who adopted a deep learning strategy, yielding a sensitivity of 82.6%. In contrast, 53 of the 122 students who adopted a surface learning strategy were correctly classified, resulting in a specificity of 43.4%. Overall, the model correctly classified 205 of the 306 students, corresponding to an overall classification accuracy of 67.0%. The balanced accuracy was 63.0%, calculated as the average of sensitivity and specificity. These results indicate that the model was considerably more effective in identifying deep learners than surface learners.

Table 4: Classification Performance of the Final Binary Logistic Regression Model

Observed learning strategy	Predicted		Percentage Correct classified
	Predicted Surface learning Strategy (0)	Predicted Deep learning Strategy (1)	
Surface learning Strategy (0)	53	69	43.4%
Deep learning Strategy (1)	32	152	82.6%
Overall Percentage			**67.0%**

DISCUSSION

This study examined whether multidimensional attitudes toward statistics predicted undergraduate students' adoption of deep rather than surface learning strategies. The final binary logistic regression model retained three statistically significant predictors: effort, interest, and perceived difficulty. Among these dimensions, effort and interest were positively associated with deep learning strategy adoption, whereas perceived difficulty was negatively associated with it. Affect, cognitive competence, and value did not make statistically significant unique contributions after the other attitudinal dimensions were considered.

Effort emerged as the strongest positive predictor of deep learning strategy adoption. This finding is theoretically consistent with the characteristics of deep learning, which requires sustained engagement, self-regulation, and a willingness to work through conceptual challenges rather than relying primarily on procedural memorisation [9], [10], [12]. Students who invest greater effort in learning statistics may be more willing to devote the cognitive resources required to connect statistical concepts, interpret analytical outputs, and apply statistical knowledge to authentic problems. Thus, effort may represent more than a general study habit; within statistics education, it may function as an important behavioural mechanism through which positive attitudes are translated into deeper engagement with learning.

Interest was also positively associated with deep learning strategy adoption. This result is consistent with evidence linking positive attitudes toward statistics with greater engagement and academic achievement. For example, Guo et al. [19] reported positive relationships between learning achievement and several SATS-36 dimensions, including affect, cognitive competence, value, interest, and effort, whereas perceived difficulty was negatively related to achievement. Another study [20] found that participation in an introductory statistics course could produce changes in several attitudinal dimensions, suggesting that students' attitudes are responsive to instructional experiences rather than being fixed personal characteristics. The present study extends this literature by demonstrating that interest remained a significant predictor of deep learning strategy adoption even after effort and perceived difficulty were statistically controlled. This finding suggests that students who are curious about statistics and perceive the subject as engaging are more likely to seek conceptual understanding rather than depend on surface-level memorisation.

Perceived difficulty was negatively associated with deep learning strategy adoption. Holding interest and effort constant, students who perceived statistics as more difficult had lower odds of adopting a deep rather than a surface learning strategy. High perceived difficulty may discourage students from engaging with complex statistical ideas and may instead encourage short-term coping strategies, such as memorising formulas or reproducing procedures without developing conceptual understanding. This interpretation is consistent with research showing that perceptions of difficulty and statistics anxiety may undermine confidence, achievement, and the overall statistics-learning experience [1], [19], [21]. It is also consistent with the systematic review by Mendes et al. [22], which concluded that interventions targeting self-efficacy and attitudes show promise, although evidence regarding the reduction of statistics anxiety remains mixed.

Affect, cognitive competence, and value were not retained in the final reduced model. This result does not necessarily indicate that these dimensions are unimportant. They may be associated with learning strategies at the bivariate level, but their unique adjusted effects may become weaker when effort, interest, and perceived difficulty are included simultaneously. One possible explanation is conceptual overlap among the attitudinal dimensions. For example, students who feel competent in statistics or recognise its value may express these attitudes behaviourally through greater effort and interest. Measurement overlap among the SATS-36 dimensions may also contribute to the attenuation of their independent effects, as suggested in previous examinations of the instrument's factor structure [23], [24]. The nonsignificant adjusted effects should therefore be interpreted cautiously rather than as evidence that affect, cognitive competence, and value have no role in statistics learning.

Instructional Implications

The findings suggest three instructional priorities for introductory statistics courses. First, course design should provide repeated opportunities for effortful practice rather than relying predominantly on one-time, high-stakes assessments. Low-stakes quizzes, guided data-interpretation activities, structured problem-solving exercises, and iterative feedback may help students sustain effort and develop more consistent engagement with statistical concepts. Second, instructional examples should be connected to students' disciplinary interests and real-life contexts to strengthen interest and perceived relevance. The use of authentic datasets, field-specific applications, and meaningful research questions may encourage students to engage more deeply with statistical reasoning rather than viewing statistics as an isolated procedural subject.

Third, instructors should seek to reduce students' perceptions of excessive difficulty without lowering conceptual expectations. Scaffolding, worked examples, visual representations, prerequisite support, and explicit guidance in interpreting statistical software output may help students progress from procedural compliance to conceptual understanding. The aim is not to make statistics superficially easy, but to remove avoidable sources of difficulty arising from unclear notation, decontextualised examples, insufficient foundational support, and assessment practices that reward memorisation more than reasoning. These instructional strategies are consistent with evidence suggesting that improvements in attitudes, self-efficacy, and engagement may require targeted pedagogical and psychological support in addition to changes in content coverage [22]. Nevertheless, because the present study employed a cross-sectional design, these implications should be interpreted as pedagogically informed recommendations rather than evidence of causal effects.

CONCLUSION

This study achieved its primary objective by applying binary logistic regression to examine whether multidimensional attitudes toward statistics predicted undergraduate students' adoption of deep rather than surface learning strategies. The findings showed that effort, interest, and perceived difficulty were significant predictors of learning strategy adoption. Students who reported greater effort and stronger interest in statistics had higher odds of adopting a deep learning strategy, whereas students who perceived statistics as more difficult had lower odds of doing so. Among the significant predictors, effort exerted the strongest effect, underscoring the importance of sustained engagement in promoting meaningful learning in statistics education. These findings suggest that introductory statistics courses should provide structured opportunities to strengthen students' effort and interest while reducing avoidable perceptions of difficulty.

Limitations and Future Research Directions

This study has several limitations. First, its cross-sectional design captured students' attitudes and learning strategies at a single point in time, thereby limiting causal inference and the examination of changes across the learning process. Second, convenience sampling was used, and participants were drawn from two regional campuses of a single Malaysian public university. Consequently, the findings may not be fully generalisable to students from other institutions, academic disciplines, educational systems, or national contexts. Third, the study relied on self-reported measures, which may be affected by social desirability, recall error, and inaccurate self-assessment. In addition, converting learning-strategy scores into a dichotomous outcome using a median-split procedure may have reduced variability and classified students with similar scores into different categories. The use of backward elimination may also produce a sample-specific model and underestimate the potential contribution of predictors excluded from the final model. Therefore, the results should be interpreted as predictive associations within the present sample rather than as definitive causal or universally generalisable relationships.

Future research should employ longitudinal designs to examine how students' attitudes toward statistics and learning strategies develop throughout a course or academic programme. Experimental or quasi-experimental studies could also evaluate whether targeted instructional interventions improve interest, effort, perceived difficulty, and deep learning. Expanding the sample to include students from multiple public and private universities, academic disciplines, and geographical regions would enhance the representativeness and external validity of the findings. Future studies may also retain learning-strategy scores as continuous variables or use latent-variable methods to preserve information and examine more nuanced relationships. Finally, integrating quantitative surveys with qualitative methods, such as semi-structured interviews or focus groups, could provide deeper insight into the experiences, beliefs, and motivations underlying students' attitudes toward statistics and their learning-strategy choices [25].

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