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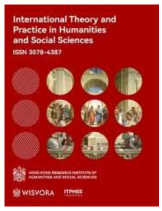


# The Construction and Application of a Differentiated Model for Middle School Mathematics Differentiated Instruction Based on the AHP Theory

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**Abstract**

The impact of differentiated standards on differentiated instruction is crucial. This study adopts a differentiated model based on the theory of analytic hierarchy process, which comprehensively considers factors such as students' learning cognition, gender, learning interest, learning experience, and learning strategies. The calculation formula for layered value L:
L=1.8or1.2+C·43%+(100I/15)·14%+[20(5-An)/3]·7%+20At/3·7%+20M/3·7%+
(100I/160)·33%(Note:1.8 for boys and 1.2 for girls). Through a teaching control experiment, it is found that differentiated instruction based on mathematical academic performance can significantly improve the learning performance of students at weak level C, while differentiated instruction based on AHP differentiated model can significantly improve the learning performance of students at weak level C and general level B. At the same time, the differentiated model based on AHP has a more stable and less volatile learning performance than the differentiated model based on mathematical academic performance.

## 1. Introduction

With the proliferation of basic education and the diversification of social life in China, individual differences among students have become increasingly apparent. Taking the learning of junior high school mathematics as an example, these differences are primarily manifested in grade-level disparities, gender differences, and proficiency variations. When a unified teaching objective is applied across the board, it often leads to two extremes: high-ability students feeling undernourished while low-ability students feeling overburdened(Xiu-feng & Dian-zhi, 2007). The Mathematics Curriculum Standards for Compulsory Education (2022 Edition) also explicitly states that the mathematics curriculum should aim to fulfill the objectives of compulsory education, cater to all students, accommodate individual differences in student development, and ensure that everyone receives quality mathematics education, with each person achieving distinct development in mathematics. Consequently, in practical teaching, teachers should take these objectively existing differences into account and rationally design teaching objectives, classroom implementation, after-school assignments, and assessments, thereby enabling every student to learn adequately and progress continuously within their zone of proximal development(Qiu-qian, 2000).

The first step in implementing differentiated instruction for students is to determine the levels of instruction. Currently, the determination of levels in differentiated instruction primarily relies on students' learning abilities, yet there is a relative lack of quantifiable and easily operable criteria for stratification. Numerous factors beyond these influence students' academic performance, particularly in mathematics. A study by Lian-ming et al.(Lian-ming & Chun-xia, 2016) revealed that, in terms of academic achievement in junior high school mathematics, girls generally outperform boys, with boys demonstrating a greater variance in overall scores. Additionally, at the lower academic levels, the proportion of boys is significantly higher than that of girls. This research(Jia-xia et al., 2000) underscores the significant impact of gender on differentiated instruction. Furthermore, students' learning strategies (mathematical cognitive strategies, mathematical metacognitive strategies, and mathematical resource management strategies) and learning experiences (learning anxiety, learning attitudes, and motivation) also play crucial roles in their mathematical learning. Based on studies by Hu Gui-ying(Gui-ying & Bai-hua, 2003), Yang Haibo (Hai-bo et al., 2015), and others(Jia-xia et al., 2000), learning strategies contribute as much as 15 to 18% to academic performance in mathematics. Regarding learning experiences, Run-sheng et al.(Run-sheng et al., 2006) found that students in the high-anxiety group had the worst academic performance, while those in the moderate-anxiety group performed best. Anxiety draws individual attention and increases working memory load, thereby reducing the working memory capacity originally allocated to mathematical operations. Learning anxiety exhibits a significant negative correlation with academic performance, while learning attitudes and motivation show a significant positive correlation. This study incorporates all major factors influencing students' academic performance, namely learning cognition (or learning foundation), gender, learning interest, learning experiences, and learning strategies, into the consideration for differentiated criteria, aiming to develop a quantifiable differentiated model.

## 2. Literature Review

### 2.1 AHP Theory

In the early 1970s, T.L. Satty(Satty, 1970), an American operational researcher, introduced a decision-making analysis method that combines qualitative and quantitative approaches, known as the Analytic Hierarchy Process (AHP)(Chandran et al., 2005). This is a semi-quantitative and modeled approach. When researchers utilize this method, they decompose complex problems into several factors and levels, calculate and compare the various elements and levels to obtain the weights of different alternatives, and subsequently select the optimal solution.

The AHP theory has been widely applied in teaching evaluation. ZHUANG Qian-qian(Qian-qian, 2022) established an online teaching effectiveness evaluation system as the overall goal layer, with teaching content, methods, modes of instruction, student characteristics, online platforms, and teacher characteristics serving as the criterion layer. She determined the evaluation system for online courses using the AHP approach. Both HUANG Yi-zhao(Yi-zhao & Ji-bing, 2022) and WU Xiao-peng(Xiao-peng & Qi-ping, 2020) built comprehensive difficulty models for college entrance examination questions based on AHP theory, and both successfully predicted the science section of the college entrance examinations in 2019 and 2021.

## 2.2 A Differentiated Model Based on the AHP Theory

The differentiated model in this study considers five factors: learning cognition(Wen-jun & Jian-sheng, 2009), student gender(Lian-ming & Chun-xia, 2016), learning interest(Hong-Yan & Xiao-lin, 2017), learning experience(Run-sheng et al., 2006), and learning strategies(Hai-bo et al., 2015; Jia-xia et al., 2000). Each factor is divided into different levels based on its unique characteristics, as defined in Table 1.1.

Table 1.1: Definitions of Stratification Criteria

| Factor | Level | Definition |
|---|---|---|
| Learning Cognition | / | Encompasses comprehension, application, and analysis. Comprehension: Understanding mathematical concepts/principles, including describing and explaining processes. Application: Employing mathematical concepts/principles in solving specific problems. Analysis: Identifying solution pathways within complex contexts and interpreting outcomes. |
| Gender | Male | Biologically identified as male. |
| | Female | Biologically identified as female. |
| Learning Interest | / | A student's comprehensive manifestation of affective experience toward mathematics learning activities, self-assessment of mathematical knowledge mastery and application, perception of mathematics' value, and autonomous engagement in learning. |
| Learning Experience | Learning Anxiety | Mathematics-specific anxiety: An unpleasant emotional state arising from apprehension toward mathematics learning and application activities. |
| | Learning Attitude | A learner's cognitive appraisal, affective response, and behavioral inclination toward mathematics learning. |
| | Learning Motivation | The internal drive energizing and directing student engagement in mathematics learning. |
| Learning Strategy | Cognitive Strategy | Techniques for rehearsing, organizing, and elaborating mathematical content (e.g., rehearsal, organization, elaboration). |

Continued table 1.1: Definitions of Stratification Criteria

| Factor | Level | Definition |
|---|---|---|
| | Metacognitive Strategy | Techniques for planning, monitoring, and regulating mathematics learning activities. |
| | Resource | Techniques for seeking assistance and managing |

| | |
|---|---|
| Management Strategy | time/learning environments. |

In terms of evaluating these factors, standardized math scores are commonly used to assess learning cognition. Student gender is categorized into male and female. Learning interest is evaluated using the learning interest questionnaire by Hai-bo et al(Hai-bo et al., 2015). To measure the three levels of learning experience—learning anxiety, learning attitude, and learning motivation—we adopt the mathematics learning experience questionnaire by Run-sheng(Run-sheng et al., 2006). Finally, for learning strategies, a Chinese-version questionnaire for Chinese middle school students based on the work of Berger and Karabenick(Berger & Karabenick, 2011) is utilized to investigate the levels of learning strategies.

Based on the Table 1-1, this study developed the hierarchical indicator system framework for the stratification model grounded in AHP theory, as depicted in Figure 1-1.

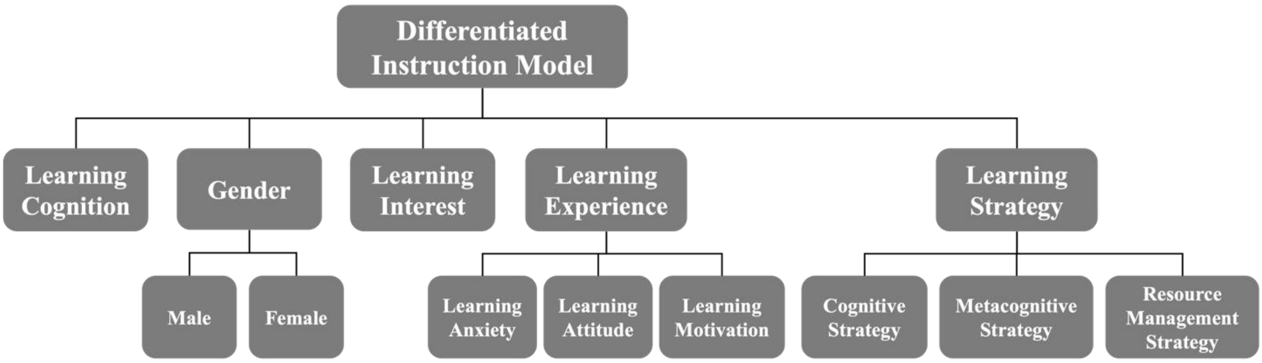


*Figure 1.1: Hierarchical Indicator System Framework Based on AHP Theory*

## 3. Methodology and Procedures

### 3.1 AHP-Based Weight Determination

(1) Construction of the Judgment Matrix

Before calculating the weight coefficients of different influencing factors, it is necessary to rank the importance of different indicators. The ranking typically uses a 9-point scale, as shown in Table 1.2.

Table 1.2: Indicator Rating Scale

| Scale | Connotation |
|---|---|
| 1 | When comparing two indicators, they are of equal importance |
| 3 | When comparing two indicators, the former is slightly more important than the latter |
| 1/3 | When comparing two indicators, the latter is slightly more important than the former |
| 5 | When comparing two indicators, the former is more important than the latter |
| 1/5 | When comparing two indicators, the latter is more important than the former |
| 7 | When comparing two indicators, the former is significantly more important than the latter |
| 1/7 | When comparing two indicators, the latter is significantly more important than the |

| | |
|---|---|
| | former |
| 9 | When comparing two indicators, the former is more important than the latter |
| 1/9 | When comparing two indicators, the latter is more important than the former |

Based on the above rating scale, a judgment matrix $A$ can be established.

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{2n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix}$$

(2) Calculation of Weight Coefficients

Step 1, perform row-wise product calculation for the judgment matrix $A$:$A_i = \prod_{i=1}^{n} a_{ij}$.

Step 2, take the $n$-th root of $A_i$: $\overline{a_i} = \sqrt{A_i}$.

Step 3, Conduct standardization processing for $\overline{a_i}$: $a_i = \frac{\overline{a_i}}{\sum_{j=1}^{n} \overline{a_j}}$.

Step 4, Calculate the weight coefficient $k_i$: $k_i = ma_i$.

(3) Consistency Test of Weight Coefficients

The Consistency Ratio ($CR$) is usually used as the consistency test index,

$$CR = \frac{\lambda_{max} - n}{RI(n-1)}$$

where $RI$ is the Random Consistency Index, $\lambda_{max} = \frac{1}{n}\sum_{i=1}^{n} \frac{Ak_i}{k_i}$. The values of $RI$ are shown in Table 1.3. If $CR$≤0.1, the weight coefficients have satisfactory consistency; otherwise, they need to be verified and adjusted by experts until satisfaction is achieved.

Table 1.3: Values of the Random Consistency Index $RI$

| Number of Indicators | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| $RI$ | 0.00 | 0.00 | 0.52 | 0.89 | 1.12 | 1.26 | 1.36 | 1.41 | 1.46 |

(4) Construction of Individual Weight Coefficients

To obtain relatively reasonable weight coefficients, the expert method was utilized to construct the judgment matrix. In the research process, 10 different experts (all of whom are mathematics teachers) were invited to provide evaluations, and rating scale data were obtained.

## 3.2 Experimental Design of a Stratified Model Using AHP

To longitudinally assess the efficacy of differentiated mathematics instruction in junior secondary education, this study implemented a class-based experimental design involving four cohorts (Classes 9-2, 9-3, 9-4, and 9-5) at MS School in Shenzhen's Yantian District in China, where the independent variable constituted stratification criteria while academic performance metrics served as the dependent variable. The control group (Class 9-2) received standard undifferentiated instruction, whereas Experimental Group 1 (Classes 9-3/4/5) underwent cognition-based stratification and Experimental Group 2 (the same Classes 9-3/4/5) experienced

AHP-model stratification, with all experimental procedures following the sequence detailed in Figure 1.2.

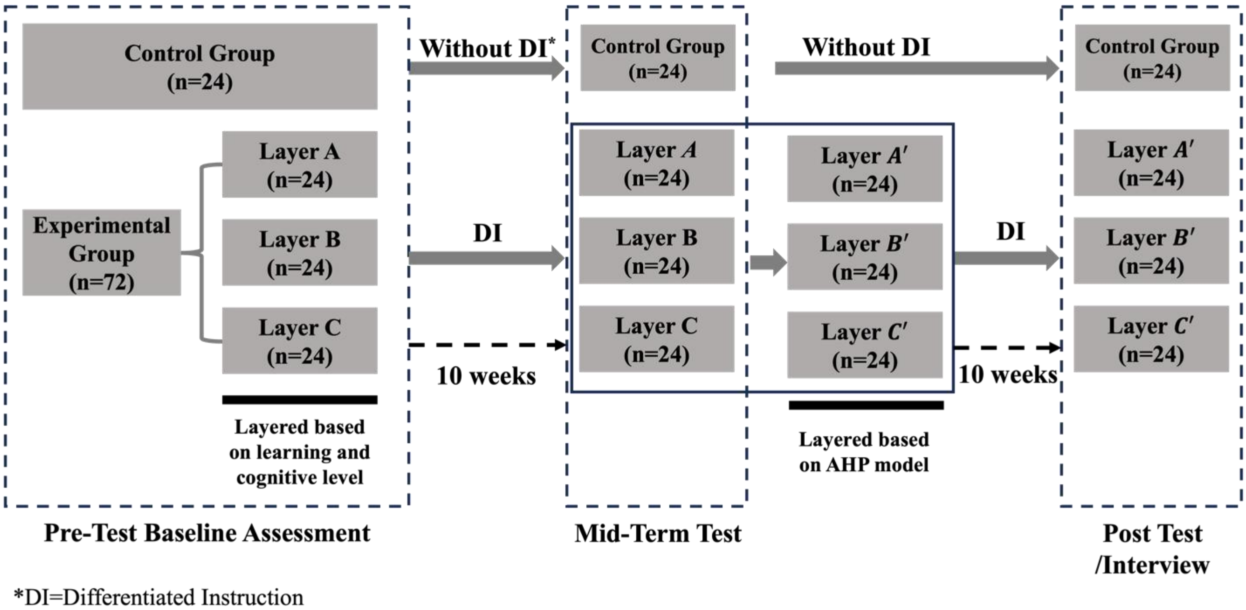


*Figure 1.2: Experimental Flowchart of Differentiated Instruction*

As illustrated in Figure 1.2, baseline assessments aligned with Shenzhen's standardized senior high school entrance examinations were administered at the beginning of the academic term. Subsequent stratification initially employed conventional learning cognition criteria - categorizing students into Tier A (≥90%), Tier B (70-89%), and Tier C (<70%) based on pre-test performance. Following a half-semester intervention implementing differentiated instruction protocols, mid-term evaluations prompted stratification restructuring using the AHP model, wherein revised thresholds defined Tier A (≥70%), Tier B (60-69%), and Tier C (<60%). The latter half-semester maintained identical instructional standards with continued tiered delivery, culminating in final assessments. All evaluation metrics utilized percentage-based scoring systems. Class-level data underwent descriptive analysis (Mean ± SD) with inferential statistical testing applied to intergroup comparative analyses.

### 3.3 Semi-Structured Student Interviews

To gain nuanced insights into perspectives on differentiated instruction practices in junior secondary mathematics classrooms, semi-structured interviews were conducted with four learners from Classes 3, 4, and 5 of Grade 9 at MS Middle School following a full-semester implementation of stratified pedagogy.

## 4. Results and Discussion

### 4.1 AHP-Based Algorithmic Encoding for Stratified Modeling

Using the calculation approach described in session 3.1, the results for ten teachers were averaged to approximate the values presented in Table 1.4. Therefore, the judgment matrix $A$ for the different factors is:

$$A = \begin{bmatrix} 1 & 9 & 5.67 & 7 & 0.71 \\ 1/9 & 1 & 0.14 & 0.20 & 0.14 \\ 0.18 & 7.12 & 1 & 2.73 & 0.45 \\ 1/7 & 5 & 0.37 & 1 & 0.23 \\ 1.41 & 7.14 & 2.22 & 4.35 & 1 \end{bmatrix}$$

Table 1.4: Scale values for each factor

| Coding | $a_{12}$ | $a_{13}$ | $a_{14}$ | $a_{15}$ | $a_{23}$ | $a_{24}$ | $a_{25}$ | $a_{34}$ | $a_{35}$ | $a_{45}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| Average value | 9 | 5.67 | 7 | 0.71 | 0.14 | 0.20 | 0.14 | 2.73 | 0.45 | 0.23 |

Remark: keep the result with 2 decimal places if not integer.

Utilizing the software yaanp (v.12.9, Shanxi Yuan Decision Software Technology Co., Ltd., Shanxi, China), the weight coefficients $k_i$ for the five elements were calculated based on matrix $A$, yielding the following values: $k_i$= 0.4201, 0.0291, 0.1449, 0.0760, 0.3298, as illustrated in Figure 1.3. The consistency ratio (CR = 0.045) obtained from the consistency check procedure is less than the threshold 0.1, indicating satisfactory consistency for the results.

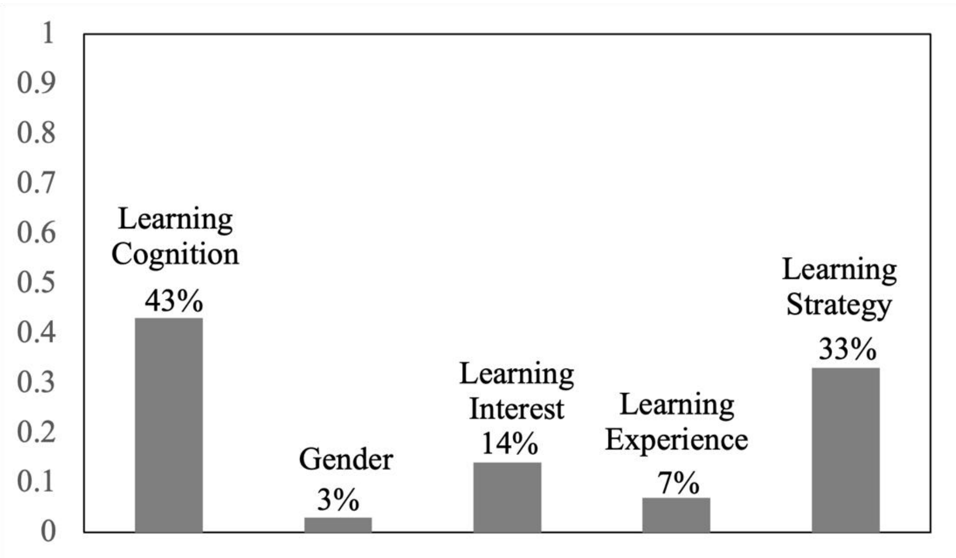


*Figure 1.3: Relative Magnitudes of Factor Weights*

Furthermore, Figure 1.3 revealed the relative influence of factors on student differentiation levels, ranked in descending order: learning cognition, learning strategies, learning interest, learning experience, and gender. Notably, learning cognition and learning strategies exerted the most significant influence, while the contribution of gender is minimal, accounting for approximately 3%.

Based on expert assessments of differentiation levels and the AHP theory's weight calculation methodology, the derived weight assignments were detailed in Table 1.5.

Based on the computed weight assignments, the relative proportions of weights across differentiation levels were presented in Figure 1.4. Consistency checked yielded the following ratios: $CR_1$=0, $CR_2$=0.054, $CR_3$=0.0024. As all values were below the 0.01 threshold, the weight coefficients demonstrate adequate consistency across differentiation levels.

Table 1.5: Scale values for each factor

| Factor | Gender | | Learning Experience | | | Learning Strategy | | |
|---|---|---|---|---|---|---|---|---|
| Average | 1.67 | | 0.15 | 0.20 | 2.71 | 1.67 | 2.07 | 1.44 |
| $A$ | $\begin{bmatrix} 1 & 1.67 \\ 0.60 & 1 \end{bmatrix}$ | | $\begin{bmatrix} 1 & 0.15 & 0.20 \\ 6.67 & 1 & 2.71 \\ 5 & 0.37 & 1 \end{bmatrix}$ | | | $\begin{bmatrix} 1 & 1.67 & 2.07 \\ 0.60 & 1 & 1.44 \\ 0.48 & 0.69 & 1 \end{bmatrix}$ | | |
| Weight | 0.0182 | 0.0109 | 0.0057 | 0.0224 | 0.0479 | 0.1579 | 0.0726 | 0.0994 |

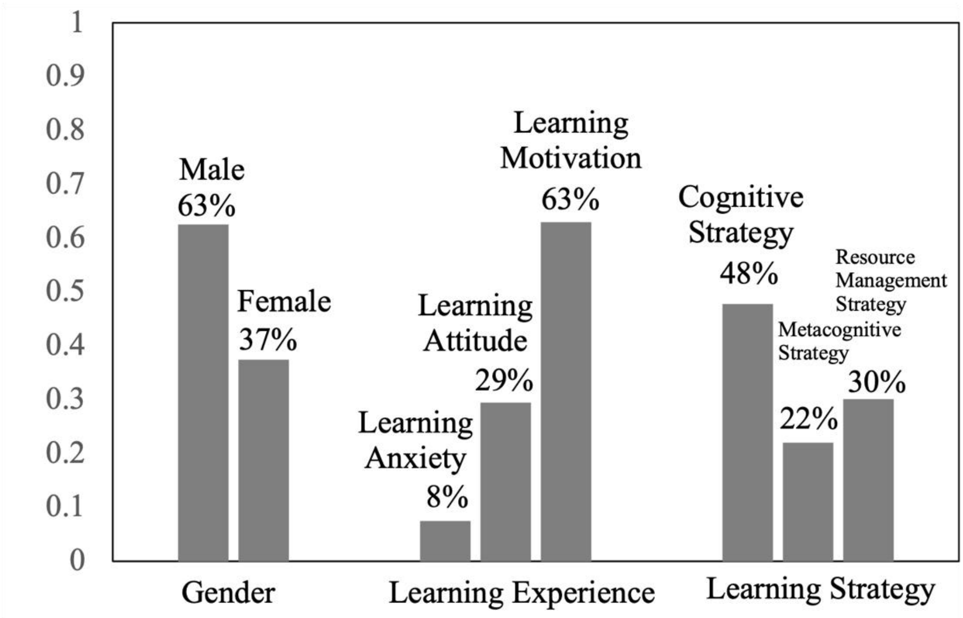


*Figure 1.4:Relative Magnitudes of Weights Across Differentiation Levels*

Building upon the preceding statistical procedures, the stratification coding scheme derived from AHP theory is presented in Table 1.6.

Table 1.6: AHP-Based Stratification Coding Framework

| Factor/500 | Weight | Input | Output | Level of Layer |
|---|---|---|---|---|
| Learning Cognition/100 | 43% | Cognition(C)/100 | C×43% | L=1.8(or 1.2)+<br>C×43%+<br>(100I/15)×14%+<br>[20(5-An)/3]×7%+<br>20At/3×7%+<br>20M/3×7%+<br>(100I/160)×33% |
| Gender/100 | 3% | Male | 1.8 | |
| | | Female | 1.2 | |
| Learning Interest/100 | 14% | I/15 | (100I/15)×14% | |
| Learning Experience/100 | 7% | Anxiety(An)/5 | [20(5-An)/3]×7% | |
| | | Attitude(At)/5 | 20At/3×7% | |
| | | Motivation(M)/5 | 20M/3×7% | |

Continued table 1.6: AHP-Based Stratification Coding Framework

| Factor/500 | Weight | Input | Output | Level of Layer |
|---|---|---|---|---|
| Learning Strategy/100 | 33% | S/160 | (100I/160)×33% | |

### 4.2 Performance-Based Academic Recordation

The experimental period spanned one full semester. Disruptions such as student transfers, illnesses, and absences occurred during this time. To ensure valid data comparisons, the analysis focused on students from four classes who had complete assessment records across all three time points: the pre-test, mid-term test, and post-test. Control Group (n=20): Pre-test scores were 65±18; Mid-test scores were 65±20; Post-test scores were 71±16. Experimental group results were detailed in Table 1.7. Notably, mid-test values differed between Table 1.7-(a) and 1.7-(b) because they represented distinct student cohorts.

Table 1.7: Effects of Stratification Criteria on Student Academic Performance

(a) Impact of Single-Criterion Stratification (Learning Cognition) on Mathematics Performance

| Class | A | | B | | C | |
|---|---|---|---|---|---|---|
| | Pre-Test | Mid-test | Pre-Test | Mid-test | Pre-Test | Mid-test |
| 9-3(n=13) | 94±5 | 99±2 | 75±4 | 79±18 | 56±6 | 66±7* |
| 9-4(n=15) | 91±1 | 89±11 | 73±3 | 71±11 | 51±11 | 62±19 |
| 9-5(n=15) | 95±7 | 94±8 | 75±6 | 87±18 | 47±12 | 54±20 |

(b) Impact of AHP-Model-Based Stratification on Mathematics Performance

| Class | $A'$ | | $B'$ | | $C'$ | |
|---|---|---|---|---|---|---|
| | Mid-test | Post-test | Mid-test | Post-test | Mid-test | Post-test |
| 9-3(n=13) | 97±5 | 96±6 | 64±6 | 77±7** | 75±0 | 88±0 |
| 9-4(n=15) | 78±20 | 81±8 | 77±11 | 77±9 | 53±12 | 61±12 |
| 9-5(n=15) | 92±9 | 91±8 | 73±16 | 80±6 | 40±5 | 56±9** |

Remark: Analysis was performed using one-way ANOVA in SPSS. Asterisks denote statistical significance between comparison groups:* indicates a significant difference ($p<0.05$).** indicates a highly significant difference ($p<0.01$).

Analysis of Table 1.7-(a), 1.7-(b), and the control group data revealed that implementing differentiated instruction yielded no statistically significant impact on Tier A students. However, a significant improvement trend was observed for Tier C students in specific classes. Furthermore, in classes stratified using the AHP model, differentiated instruction also demonstrated a statistically significant positive effect on Tier B students. These findings indicated that differentiated instruction significantly enhanced academic performance among students with weaker foundational knowledge. Concurrently, AHP-guided stratification also produced significant performance gains among average-achieving students.

Comparison of different stratification criteria showed that grouping based solely on learning cognition resulted in high data variability (large standard deviations) and substantial intra-group differences. In contrast, stratification employing the AHP model significantly enhanced data stability across all tiers. This enhanced stability was evident in the mid-test data for Tiers B and C (Table 1.7-(a)) and the post-test data for Tiers B and C (Table 1.7-(b)) across the three classes. The underlying reason was likely attributable to the single-criterion nature of learning cognition-based stratification. Since academic performance is multifactorial, this approach yielded fewer stable outcomes. Conversely, the AHP model incorporated key determinants of mathematics performance—learning cognition, gender, learning interest, learning experience, and learning strategies. This comprehensive consideration of influencing factors enhanced result stability and reduced susceptibility to interference.

### 4.3 Protocol-Driven Interview Documentation

Interview excerpts revealed consistently positive student perspectives toward tiered differentiation:

Student 1 expressed strong appreciation for completing ability-appropriate assignments within my competency range, noting heightened teacher attention during instruction. Student 2 reported unexpected promotion to Tier A despite moderate midterm performance, describing this upward mobility as motivational toward exemplifying tier-appropriate standards. Student 3 (Tier C) proactively requested supplementary Tier B materials to maintain aspirational momentum, explicitly targeting progression in subsequent assessments. Crucially, Student 4 indicated no perceived stigmatization in Tier C, citing productive cross-tier collaboration through meaningful dialogue with peers across proficiency levels.

Collectively, these narratives validate student receptivity to stratified learning frameworks while demonstrating tangible academic outcomes. The testimonies align with quantitative findings regarding achievement gains—particularly among foundational learners—reinforcing differentiated instruction's efficacy in fostering goal-oriented engagement. Notably, the self-regulated learning behaviors observed (e.g., strategic material requests, cross-tier help-seeking) substantiate the model's capacity to cultivate metacognitive awareness beyond mere score improvement, with the dynamic tier-adjustment mechanism emerging as a critical motivational driver within this pedagogical approach.

## 5. Conclusion and Suggestion

Research findings indicate that primary determinants of junior secondary mathematics achievement encompass learning cognition levels, gender, subject interest, learning experiences, and metacognitive strategy deployment. Utilizing Analytic Hierarchy Process (AHP) modeling, factor weights for stratification were quantified as follows: learning cognition (43%), gender (3%), learning interest (14%), learning experience (7%), and learning strategies (33%). This yielded the AHP-based stratification index formula: $L=1.8 \text{or} 1.2+C\cdot 43\%+(100I/15)\cdot 14\%+[20(5-An)/3]\cdot 7\%+20At/3\cdot 7\%+20M/3\cdot 7\%+(100I/160)\cdot 33\%$(Note:1.8 for boys and 1.2 for girls). Controlled pedagogical experiments revealed that cognition-based differentiation significantly enhanced achievement in Tier C (foundation-level learners), whereas AHP-model stratification produced significant gains across both Tiers B and C.

Moreover, AHP-stratified cohorts demonstrated markedly lower score volatility ($p<0.01$), indicating superior stability relative to cognition-based approaches.

Notwithstanding these outcomes, three methodological limitations warrant future resolution. First, the semi-quantitative expert elicitation process for weighting factor importance exhibited regional bias, as localized participant pools (e.g., exclusive to Shenzhen educators) compromised objectivity through institutional and metropolitan cultural influences. Expanding expert recruitment to nationally diverse institutions would enhance validity and generalizability. Second, the negligible gender weighting (3%) suggests its potential elimination from future models, while minimal inter-level variance within learning experience components (anxiety, attitude, motivation) supports consolidating these into a unified construct. Third, although instructional heterogeneity was controlled in experimental groups (9-3/4/5) through single-instructor delivery, the control group (9-2) involved different instructors, a confounder requiring mitigation via uniform teaching assignments in subsequent trials.

These refinements address inherent complexities in pedagogical intervention research, particularly regarding instructor variables within quasi-experimental designs. Future iterations should prioritize multi-regional expert validation, model simplification through factor consolidation, and rigorous instructional standardization across all comparison groups to strengthen causal inference regarding stratification efficacy.

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