JOURNAL OF BALTIC SCIENCE EDUCATION

ISSN 1648-3898 /Print/
ISSN 2538-7138 /Online/

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PROFILING SCIENTIFIC INQUIRY SKILLS: EXPLORING RELATIONSHIPS WITH SCIENTIFIC COMPETENCY AND BACKGROUND FACTORS IN HIGH SCHOOL STUDENTS

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Abstract. *Scientific inquiry skills are crucial for scientific literacy and cognitive development in the 21st century. Prior research has identified key inquiry skills—data analytics (DA), control of variables (COV), and scientific reasoning (SR)—but has not validated these skills through comprehensive assessments. The aim of this study was to validate and examine the relationship between students' inquiry skill profiles and their scientific competency. Through latent profile analysis (LPA), this study classified 667 Taiwanese high school students into three profiles: Sophisticated, Experimental, and Basic. The Sophisticated profile demonstrated strong proficiency in DA, COV, and SR, while the Experimental profile excelled in DA with moderate COV and SR skills. The Basic profile revealed deficiencies across all inquiry skills. ANOVA results indicated significant differences in scientific competency across profiles, with Sophisticated students outperforming others. Additionally, students' majors significantly influenced profile distribution, with natural science majors more likely to be classified as Sophisticated or Experimental. No significant relationship was identified between inquiry profiles and gender, parental education, or financial status. These findings highlight the importance of reasoning skills in scientific competency and suggest the need for tailored educational interventions to enhance students' inquiry abilities. The study provides empirical evidence for the applicability of inquiry skill profiles in diverse educational contexts.*

Keywords: *latent profile analysis, scientific competency, inquiry skills, reasoning skills*

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Introduction

Inquiry skills are essential components of scientific literacy and fundamental to 21st-century cognitive competencies. These skills have garnered increasing attention in response to evolving science education standards (Abd-El-Khalick et al., 2004; Gagné, 1963; National Research Council, 2000; Zhou et al., 2016). Scientific inquiry fosters critical thinking and problem-solving, enabling students to engage in systematic exploration. Lipman (2003) has highlighted the importance of cultivating an integrated thinking approach within scientific inquiry practices. Prior research has consistently underscored key dimensions of inquiry skills, including data analytics (DA)—the ability to analyze and interpret data to derive meaningful insights, control of variables (COV)—the capacity to systematically manipulate and isolate variables to establish causal relationships, and scientific reasoning (SR)—which encompasses logical analysis, hypothesis evaluation, and evidence-based argumentation (Bao et al., 2009; Chen & Klahr, 1999; Chen et al., 2023; Kuhn & Pease, 2008; Omarchevska et al., 2022; Sui et al., 2023; Wu & Hsieh, 2007).

Beyond cognitive skills, inquiry skills also involve attitudinal dimensions that influence students' engagement and problem-solving approaches (Gibson & Chase, 2002; Windschitl, 2003). Sui et al. (2024) developed a scientific inquiry skill profile model using latent profile analysis (LPA) to classify students based on their likelihood of exhibiting distinct inquiry skill patterns (Spurk et al., 2020). Their study examined learners' performance in an animation-based activity (ABA) designed to assess DA, COV, and SR. However, while this profiling approach has identified distinct inquiry skill patterns, it did not validate these profiles through standardized assessments of scientific competency. As a result, it remains unclear whether students categorized under different profiles possess corresponding levels of domain-specific scientific knowledge. Investigating this relationship is crucial for understanding how inquiry skills translate into scientific competency in practice.

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

To address this gap, the present study integrates a formal assessment of students' scientific competencies and examines their relationship with the inquiry skill profiles identified by Sui et al. (2024). Specifically, this study employs replication research, which plays a critical role in educational research by confirming previous findings (Makel et al., 2019), identifying moderating variables (Perry et al., 2022), and expanding theoretical models to new contexts (Hedges, 2018; Morrison, 2022). This study utilizes assessment items from Inquiry in Scientific Thinking, Analytics, and Reasoning (iSTAR) alongside science examination questions from Taiwan's national secondary-level assessments. The iSTAR framework provides a structured approach to evaluating scientific reasoning across core inquiry dimensions, including DA, COV, and SR (Bao et al., 2022). By incorporating these assessments, this study sought to validate the predictive utility of inquiry skill profiles in determining students' scientific competency.

Scientific Inquiry

The National Science Education Standards (NSES) defines scientific inquiry as "the diverse ways in which scientists study the natural world and propose explanations based on evidence derived from their work" (National Research Council, 1996, p. 23). This definition aligns with various academic perspectives, which conceptualize scientific inquiry as a process involving key steps such as question formulation, hypothesis development, experimentation, planning, prediction, model utilization, data collection and analysis, result interpretation, and knowledge dissemination (Bell et al., 2010; Minner et al., 2010).

In contrast to traditional views that consider scientific competence as a sum of individual skills, contemporary global assessments—such as the Programme for International Student Assessment (PISA)—underscore a more integrative approach. PISA emphasizes that students' engagement in science learning and their ability to address real-world scientific problems require the dynamic application of multiple interrelated skills (OECD, 2017). This shift highlights the importance of understanding how students apply scientific inquiry skills rather than simply measuring isolated competencies.

Prior research (Bao & Koenig, 2019; Bao et al., 2022) has identified three core scientific inquiry skills essential for students' active participation in the learning process:

1. Data analytics (DA) – identifying trends and patterns in data to extract meaningful insights.
2. Control of variables (COV) – designing and conducting experiments by systematically manipulating variables to establish causality.
3. Scientific reasoning (SR) – linking evidence to logical conclusions through structured reasoning processes.

These skills form the foundation of scientific inquiry, equipping students with the ability to interpret data, design controlled experiments, and develop causal explanations, all of which are crucial for engaging meaningfully with scientific problems. DA refers to the ability to recognize patterns and trends within data, enabling data-driven decision-making (Gandomi & Haider, 2015). Developing DA skills allows students to analyze collected data systematically, interpret it as evidence, and draw informed conclusions about causal relationships (Bao et al., 2022).

COV is a critical experimental strategy that enables students to establish causal inferences by isolating and systematically manipulating a single variable at a time (Strand-Cary & Klahr, 2008; Tschirgi, 1980). Mastery of COV has been identified as a strong predictor of scientific competence (Bryant et al., 2015) and serves as a fundamental principle in scientific reasoning (Kuhn, 2007). Engaging in experimental setup and variable specification fosters learners' ability to conduct rigorous scientific investigations and draw valid conclusions. SR is the cognitive process of deriving conclusions from empirical evidence and logical inference (Lohman & Lakin, 2011; Zimmerman, 2007). Shaw (1996) defined reasoning as the act of linking facts and evidence to support logical conclusions. SR is integral to the scientific learning process, as it underpins hypothesis testing, systematic variable manipulation, and the evaluation of experimental outcomes (Bao et al., 2009). Through scientific reasoning, students refine their inquiry abilities by iteratively developing, testing, and revising knowledge based on observed evidence.

Latent Profile Analysis

LPA is a categorical latent variable modeling technique designed to identify latent subpopulations within a broader demographic based on shared characteristics (Collins & Lanza, 2009; Wang & Hanges, 2011). By employing probabilistic classification, LPA assigns individuals to distinct subgroups, each characterized by unique configurations of personal and situational variables. This person-centered methodology identifies typologies of individuals by analyzing patterns in observed indicators (Spurk et al., 2020), offering a structured approach to understanding

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

heterogeneity within a population. The resulting categorical latent variable models provide an effective means of capturing underlying subgroup structures, enhancing the interpretation of population diversity (Howard & Hoffman, 2018).

A key consideration in applying LPA is the determination of an appropriate sample size to ensure reliable profile identification. Simulation-based evidence indicates that a sample size of around 500 is ideal for reliable classification (Nylund et al., 2007). Additionally, selecting the most suitable profile solution requires evaluating various goodness-of-fit indices, including the Akaike information criterion (AIC), Bayesian information criterion (BIC), sample-size adjusted BIC (SABIC), bootstrapped likelihood ratio test (BLRT), and entropy (Spurk et al., 2020). Lower AIC, BIC, and SABIC values indicate a more parsimonious and better-fitting model (Weller et al., 2020). Entropy, ranging from 0 to 1, measures classification accuracy, with values above 0.8 considered satisfactory (Celeux & Soromenho, 1996; Clark, 2009). Furthermore, a significant p-value for the Lo-Mendell-Rubin likelihood ratio test (LMR-LRT) and BLRT suggests that a model with a greater number of profiles provides a superior fit compared to a more parsimonious solution.

While statistical criteria play a vital role in determining model fit, past research emphasizes the importance of integrating theoretical and substantive considerations in profile selection (Gabriel et al., 2015; Hirschi & Valero, 2017; Vermunt, 2002; Woo et al., 2018). A well-constructed LPA model should not only demonstrate strong statistical validity but also align with theoretical frameworks and empirical insights to ensure meaningful interpretation.

Recent years have witnessed a surge in LPA applications within the field of science education, reflecting its growing recognition as a valuable methodological tool. An analysis of the Scopus database (2016–2023) reveals an increasing number of studies utilizing LPA, with 16 articles published in leading journals such as the International Journal of Science Education, Science Education, Journal of Research in Science Teaching, Research in Science Education, and International Journal of Science and Mathematics Education.

Several studies illustrate the diverse applications of LPA in science education. For instance, Sui et al. (2024) employed LPA to classify 11th-grade Chinese students' inquiry skill profiles, while Galano et al. (2024) utilized LPA to identify attitudinal profiles among Italian students in grades 9–13. Additionally, Snodgrass et al. (2020) explored the mathematics and science beliefs of underrepresented student populations, leveraging LPA to examine their attitudes and perceptions. This trend highlights the increasing adoption of LPA for investigating individual differences in science learning and engagement.

The selection of LPA in this study is driven by its alignment with a person-centered approach (Bergman & Trost, 2006; Collins & Lanza, 2009), which facilitates the identification of heterogeneous learning profiles within a dataset. As a form of mixture modeling, LPA assesses the existence of multiple latent profiles by evaluating the fit of competing models (Goodman, 2002; Bowers et al., 2013). This technique is particularly advantageous for distinguishing whether students exhibit a singular pattern of inquiry skills or a mixture of distinct profiles within the target population.

By employing LPA, this study sought to explore how many distinct profiles of inquiry skills best represent Taiwanese students and examine how these profiles relate to demographic characteristics and scientific competency. This study aimed to extend existing research on inquiry-based learning by providing a refined classification system that links students' inquiry abilities with their broader academic performance.

This study contributes to the field in two significant ways. First, it replicates and validates the inquiry skill profile model, reinforcing its generalizability across diverse educational contexts. Ensuring the stability of these profiles strengthens their applicability in future research and practice. Second, this study builds upon previous work by examining how different inquiry skill profiles are associated with scientific competency. By providing empirical evidence that distinct profiles predict variations in scientific performance, this study enhanced the model's utility as both a descriptive and predictive tool. In summary, the study addressed the following research questions:

4. To what extent can the inquiry skill profiles be replicated and validated?
5. How do students' scientific competencies, as measured by iSTAR and Taiwan's national science examinations, differ across the identified inquiry skill profiles?
6. To what extent do demographic factors moderate the relationship between inquiry skill profiles and scientific competency?

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

Research Methodology

General Background

This study employed a quantitative, cross-sectional research design grounded in a person-centered analytical approach. The research aimed to validate and replicate high school students' scientific inquiry skill profiles and examine their relationship with scientific competency and demographic characteristics. Data collection occurred over two academic years (2022–2023) in a public high school located in central Taiwan. The school was purposively selected due to the representative nature of its students' academic performance in national assessments. The study utilized LPA to identify distinct subgroups of learners based on their scientific inquiry skills. The use of LPA reflects a commitment to person-centered methodologies that capture heterogeneity in learners' cognitive profiles, as opposed to traditional variable-centered approaches. To assess students' inquiry and scientific competencies, the study integrated both performance-based assessments and standardized test items from the iSTAR and CAP assessments. The scope of the research included investigating the distribution of inquiry skill profiles, their predictive validity for scientific competency, and the influence of demographic factors such as gender, academic major, family financial background, and parental education.

Sample Selection

This study examined high school students' scientific inquiry abilities, with the goal of assessing the robustness and transferability of inquiry skill profile classifications. Previous studies utilizing LPA have indicated that a minimum sample size of around 500 participants is necessary to achieve adequate model stability and estimation accuracy (Morgan, 2015). In this study, this senior high school was selected due to its representative student academic performance, as prior research has demonstrated that its students' General Scholastic Ability Test (GSAT) scores closely align with the national probability distribution (Chang & Cheng, 2008; Lin & Chang, 2017). The participants, specializing in both natural and social sciences, were purposively sampled from a centrally located school in Taiwan. Data were collected from 667 high school students (aged 15–16 years) over two consecutive years. Before data collection, informed consent was obtained from the school administration and participating students. Background information—including gender, academic major, parental education level, and family financial status—was gathered to explore potential influences on scientific inquiry skill profiles and their relationship with scientific competency.

Instrument and Procedures

Animation-based activities

The ABA integrates multiple representations, dynamic visualizations, seamless 2D-to-3D transitions, and cognitive load reduction techniques to enhance students' engagement and comprehension of scientific inquiry (Papadakis, 2022; Papadakis, Kiv, et al., 2023; Papadakis, Kravtsov, et al., 2023; Wu & Shah, 2004). This rigorously validated inquiry-based learning activity (Sui et al., 2024) was implemented in Taiwanese high schools, with content carefully translated from Simplified Chinese to Traditional Chinese to ensure accessibility and linguistic accuracy.

Developed on the CCR platform (https://ccr.tw), ABA consists of a structured sequence of learning components, including a preface, two animation experiments (AE1 and AE2), and five assessment tasks. The activity begins with an introductory preface that contextualizes the topic by discussing rising atmospheric methane levels and emphasizing methane's significantly greater heat absorption capacity compared to carbon dioxide.

The first animated experiment (AE1) presents a comparative setup featuring three bottles: Bottle A contains air and $H_2O_{(l)}$, Bottle B contains air, $H_2O_{(l)}$, and CO_2, and Bottle C contains air, $H_2O_{(l)}$, and CH_4. Following this visualization, students complete Task 1, a multiple-choice question designed to assess their DA skills by interpreting the experimental setup.

Building upon the first experiment, AE2 extends the scientific investigation by incorporating an animated procedure that simulates exposure to UV light. This simulation introduces an essential concept in atmospheric chemistry by making water vapor and hydroxyl radicals visible. After engaging with AE2, students proceed to three additional assessment tasks. Tasks 2 and 3 consist of multiple-choice questions evaluating students' DA skills. Task 4, an open-ended response item, assesses their SR abilities, requiring them to construct logical explanations based

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

on the presented evidence. Task 5, another open-ended task, measures students' COV skills, challenging them to design or evaluate experimental conditions.

The illustrations of ABA are provided below (Figures 1, 2, 3, 4, 5, 6, and 7). The original task descriptions were presented in Traditional Chinese for student activities, and the accompanying figures include English translations for clarity and accessibility.

Figure 1
The preface of the ABA

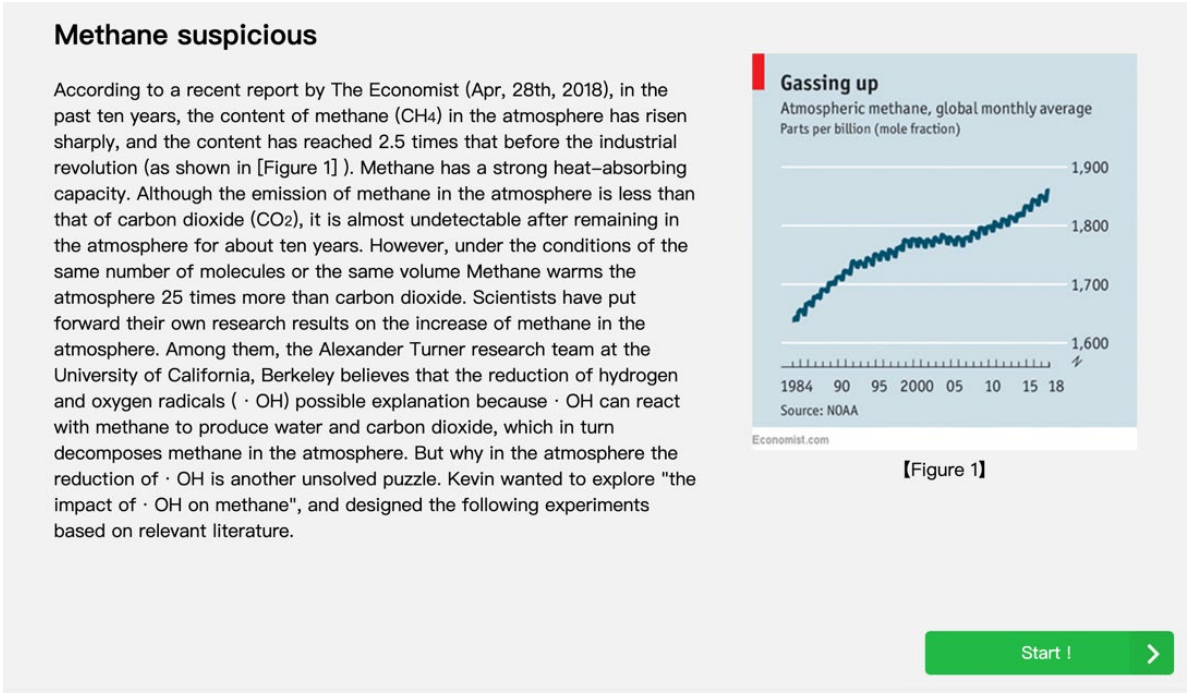
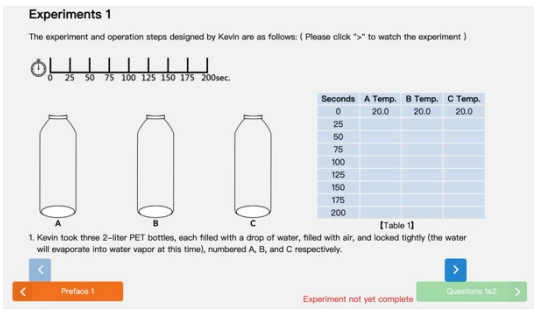
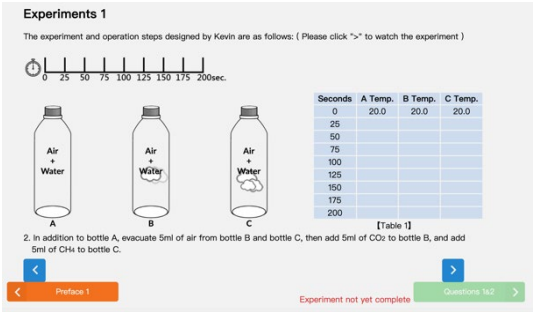


Figure 2
Animation experiment 1 (AE1)

(a)



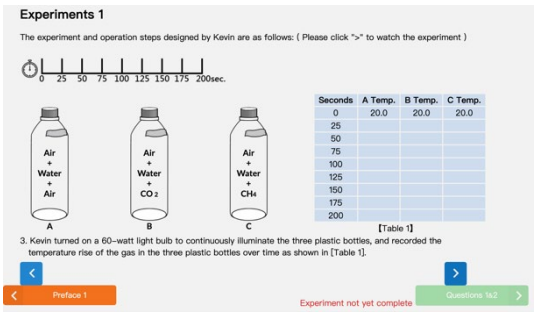
(b)



https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

(c)



(d)

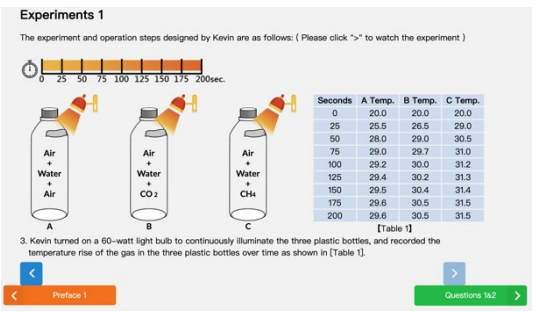


Figure 3
Task 1

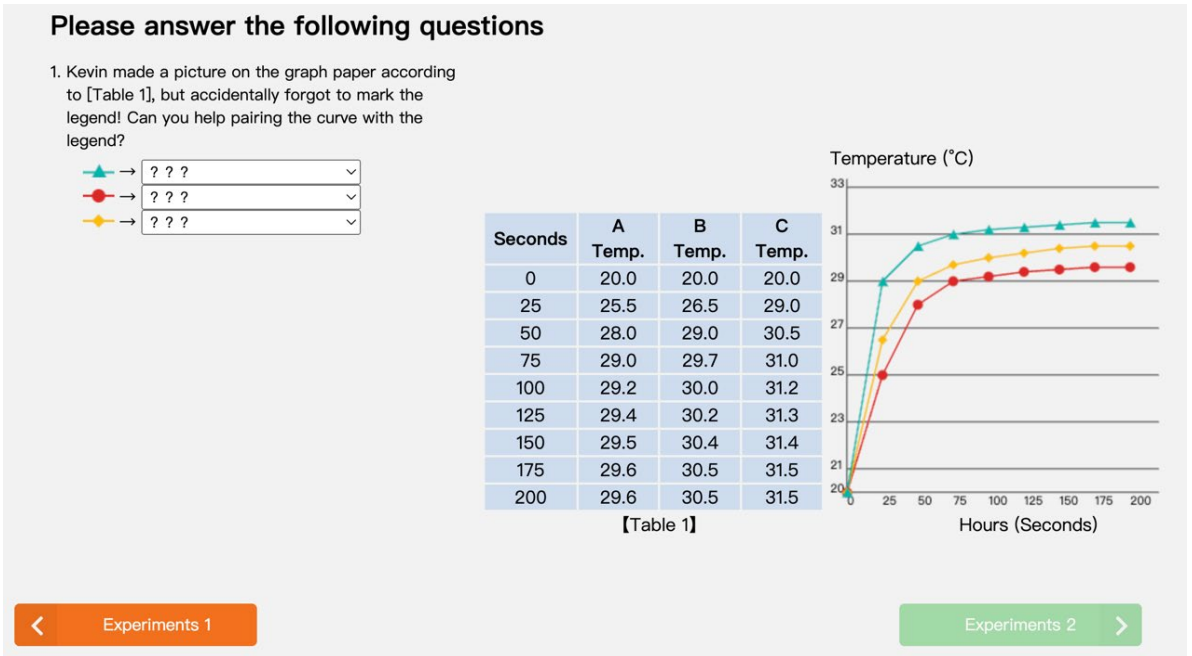
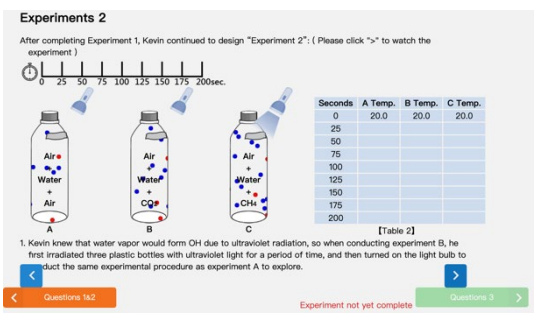
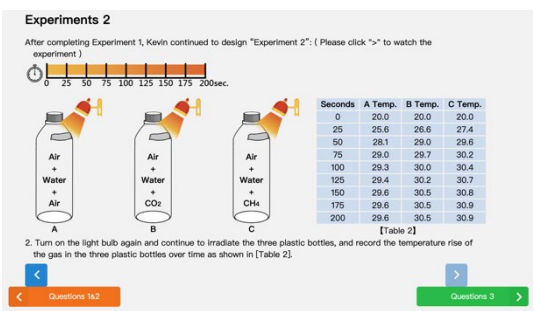


Figure 4
Animation experiment 2 (AE2)

(a)



(b)



https://doi.org/10.33225/jbse/25.24.824

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Figure 5
Task 2

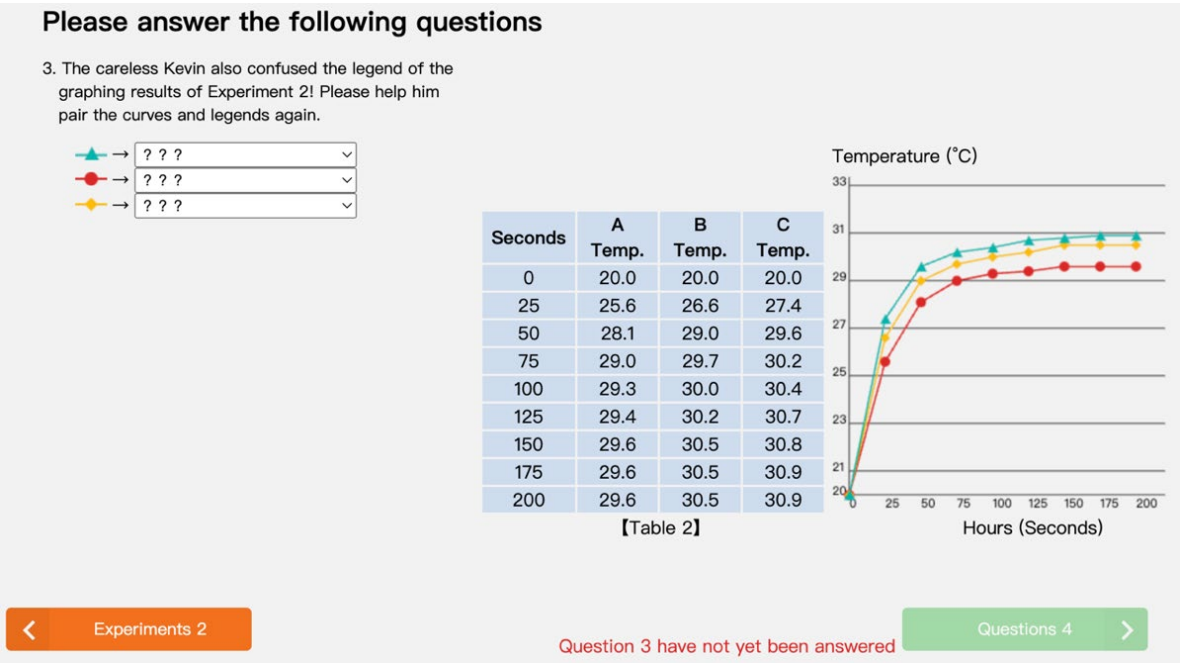
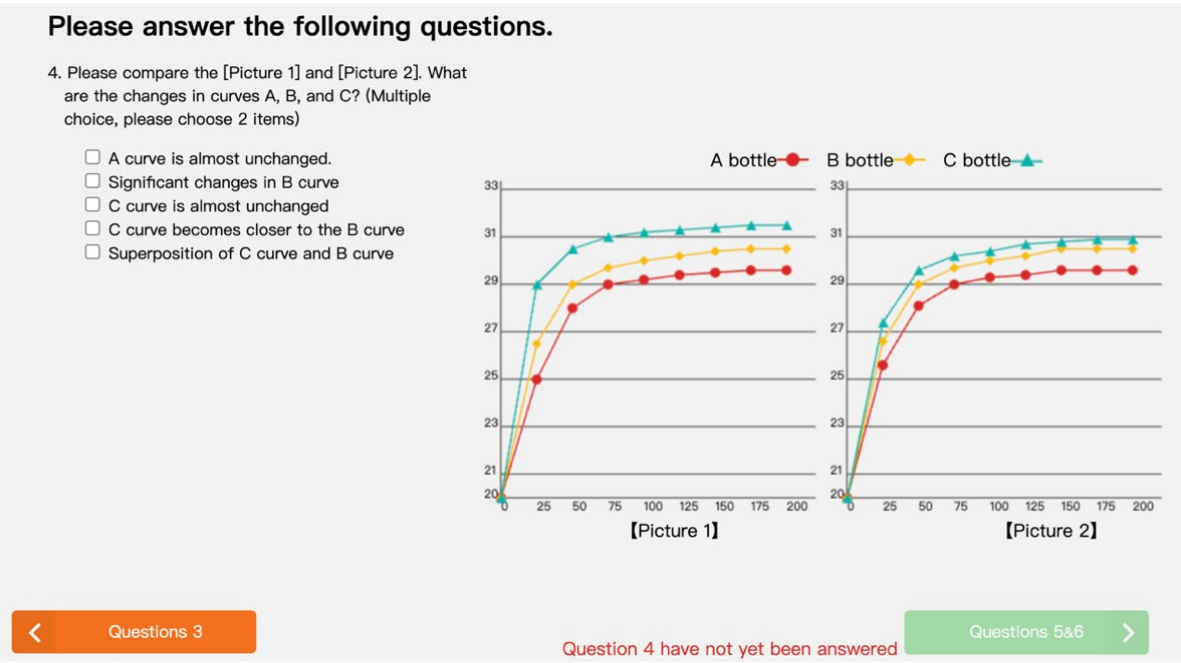


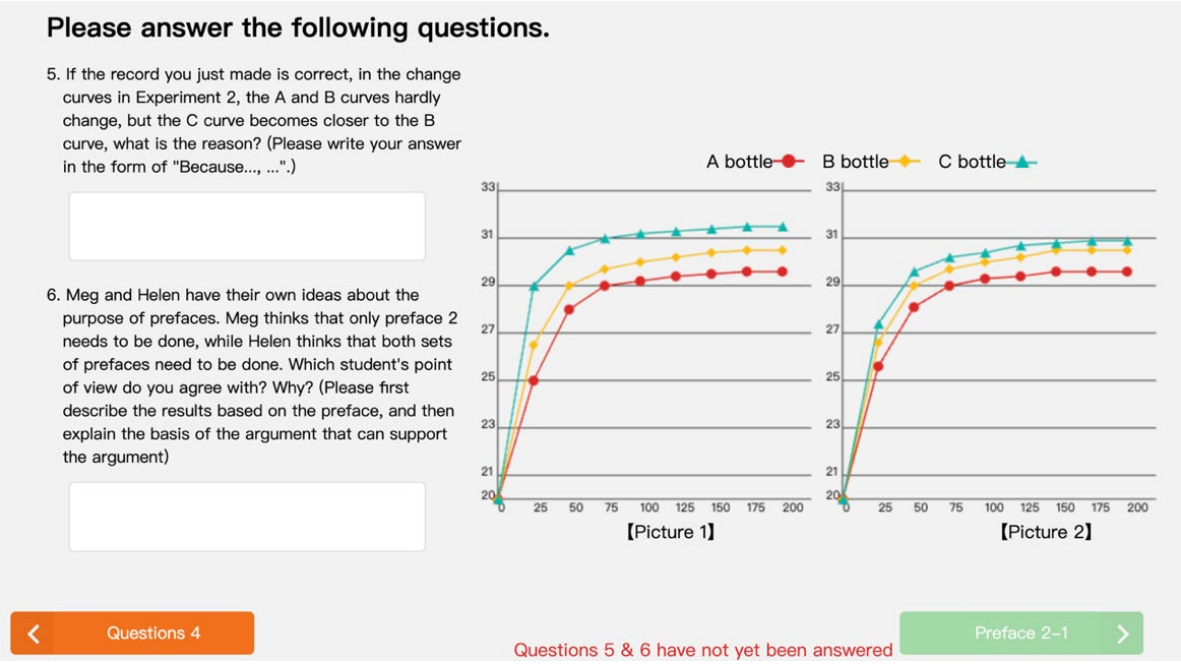
Figure 6
Task 3



https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
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Figure 7
Task 4 and Task 5



Scientific Competency Test

The Scientific Competency Test was employed to assess the relationship between students' inquiry skill profiles and their science achievement. This assessment consisted of 12 multiple-choice questions from the Taiwan Comprehensive Assessment Program (CAP) and 18 multiple-choice questions from the iSTAR assessment.

The CAP is a standardized science examination used for high school and vocational school admissions in Taiwan. Since 2012, the Taiwanese government has increasingly aligned CAP with the Programme for International Student Assessment (PISA), reflecting the growing influence of PISA rankings on educational policy and public perception (Yang & Lin, 2015). This integration has reinforced CAP's emphasis on scientific inquiry and problem-solving skills, making it a relevant measure for assessing students' science competency in line with international benchmarks.

The iSTAR assessment, developed by Bao et al. (2022), is a robust tool for evaluating scientific literacy, particularly within inquiry-based learning contexts. Over the past decade, iSTAR has undergone extensive qualitative and quantitative validation, ensuring its alignment with established science education frameworks such as PISA and TIMSS. The test assesses higher-order cognitive skills, including COV, DA, and causal decision-making, mirroring PISA's focus on explaining phenomena and designing investigations and TIMSS's emphasis on Knowing, Applying, and Reasoning (Mullis & Martin, 2013; OECD, 2017).

Unlike traditional assessments such as the Lawson Classroom Test of Scientific Reasoning (LCTSR), which have limitations in differentiation and scalability, iSTAR provides a more precise and adaptable evaluation of scientific reasoning. While originally designed for college entry and higher education assessments, its inquiry-based structure makes it well-suited for tracking the development of scientific reasoning from middle school onward. The validity and reliability of iSTAR have been rigorously tested using classical statistical methods and Rasch analysis, confirming its effectiveness in measuring scientific reasoning skills. Additionally, science education experts have reviewed and validated the assessment items to ensure construct validity, reliability, and relevance to the targeted competencies.

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

Procedures

The study was conducted during regular school hours and consisted of two phases. First, students completed the Scientific Competency Test, designed to assess their understanding of key scientific concepts and their ability to apply scientific reasoning skills. Following this, students participated in an ABA, an inquiry-driven learning module that included multiple animated experiments and assessment tasks to evaluate their inquiry skills in an interactive context.

Data Analysis

Coding Approaches

Tasks 1, 2, and 3 assessed DA skills, with each task awarding two points for correctly matching all labels. To enhance scoring efficiency, Tasks 1 and 2, which focused on recognizing covariation in data, were averaged to provide a composite score. Task 3, a multiple-choice question, evaluated students' ability to distinguish between the charts in the previous tasks by including two correct options, requiring a more nuanced understanding of data representation.

Tasks 4 and 5, designed based on established coding criteria and prior research by Sui et al. (2024), examined distinct aspects of scientific inquiry skills. Task 4 assessed mechanistic causal reasoning, requiring students to explain interactions among key variables such as UV light, water, CO_2, methane, and hydroxyl radicals. A comprehensive response is needed to logically describe how water vapor reacts with UV light to form hydroxyl radicals, which subsequently interact with methane to produce CO_2. This process results in the gas composition in Bottle C resembling that of Bottle B, with the reaction nearing completion but not fully occurring. As a result, the curve for Bottle C approaches but does not exactly match that of Bottle B.

Task 5 aligned with the study's research objective by prompting students to compare the effect of hydroxyl radicals on methane. Participants analyzed two experimental setups:

1. Experiment 1 served as the control group, featuring a 60-watt light bulb with no hydroxyl radicals.
2. Experiment 2 represented the experimental condition, incorporating UV light and hydroxyl radicals.

This task required students to identify data-covariation relationships, determine necessary experimental conditions, and specify the corresponding independent variables to establish causality. To ensure scoring reliability, the first author evaluated all responses, ensuring consistency and accuracy in grading. Additionally, two independent authors double-checked all assessments, reinforcing the validity of the scoring process.

Analytical Strategies

This study used the tidyLPA package in R (version 4.1.0; Rosenberg et al., 2019) to do LPA. Models were estimated with increasing numbers of latent groups (1 to 10), following the equal variance and zero covariance model, as alternative specifications failed to converge. The analysis produced categorical latent variables, representing students' scientific inquiry skill profiles within the dataset ($n = 667$). To validate the final class solution, the dataset was randomly partitioned into two halves (Kampa et al., 2016). LPA was then re-executed on both subsets to ensure that the derived profiles remained consistent with the original model. This step was critical for assessing the stability and replicability of the identified profiles.

To identify the associations between students' inquiry skill profiles and their science competency, χ^2 tests and cross-tabulation analyses were employed. A threshold of $p < .05$ was determined for statistical significance (Agresti, 2012; Li et al., 2023). For significant associations, additional post-hoc tests were conducted using the Bonferroni correction and standardized Pearson residuals. Absolute residual values exceeding 1.96 were interpreted as indicating a significant difference at the .05 significance level.

Research Results

Students' DA skills were assessed through three tasks, each scored on a 0 to 2 scale. Table 1 presents the descriptive statistics for each task, including minimum and maximum scores, mean values, and standard deviations. On average, students scored 4.84 out of a maximum of 6 ($SD = 1.79$) across all three tasks, indicating a moderate level of proficiency in data interpretation and pattern recognition.

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

Students' SR skills were evaluated through Task 4, which assessed four dimensions of cause-and-effect analysis. The task required students to examine the relationships among three distinct causes (C1, C2, C3) and a single effect (E1), emphasizing the interconnected nature of causal mechanisms. Each dimension was scored on a 0 to 1 scale. Table 2 provides descriptive statistics, including minimum and maximum scores, mean values, and standard deviations. Overall, students obtained an average score of 0.88 out of a maximum of 4 (SD = 1.11), suggesting difficulties in articulating mechanistic causal explanations.

Students' COV skills were assessed using Task 5, which measured two key dimensions: identifying the comparative group structure within the experimental design (CP) and recognizing the independent variable (IV). Each dimension was evaluated on a 0 to 1 scale. Table 3 summarizes the descriptive statistics, including minimum and maximum scores, mean values, and standard deviations. The average student score was 0.63 out of a maximum of 2 (SD = 0.70), indicating that students faced challenges in experimental design and variable control.

Table 1
Description of Students' DA

Task	Min	Max	*M*	*SD*
Task 1	0	2	1.51	0.86
Task 2	0	2	1.54	0.84
Task 3	0	2	1.79	0.48

Table 2
Description of Students' SR

Task		Min	Max	*M*	*SD*
Task 4	C1	0	1	0.18	0.39
	C2	0	1	0.18	0.39
	C3	0	1	0.10	0.29
	E1	0	1	0.43	0.50

Table 3
Description of Students' COV

Task		Min	Max	*M*	*SD*
Task 5	CP	0	1	0.40	0.49
	IV	0	1	0.23	0.42

Pearson correlation coefficients were computed to explore the correlation among students' performance in DA, SR, and COV skills. Table 4 presents significant positive correlations among all three inquiry skills, indicating a strong interconnection between them. There was a moderate positive correlation between DA performance and SR skills (r = .301, p < .01) as well as DA performance and COV skills (r = .249, p < .01). Additionally, a strong positive correlation was observed between SR skills and COV skills (r = .459, p < .01), suggesting that students with stronger scientific reasoning abilities tend to demonstrate better control of variables in experimental design. These findings highlight the interdependence of inquiry skills, suggesting that students who perform well in one area are likely to excel in others. The results further emphasize the importance of adopting a holistic approach to fostering inquiry skills, as interventions targeting one domain may yield broader improvements across multiple aspects of scientific inquiry.

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

Table 4
The Correlations Among Students' Performance

Inquiry skills	DA	SR	COV
DA	1		
SR	.301**	1	
COV	.249**	.459**	1

Identification of inquiry skill profiles

LPA was performed using z-transformed averages of DA, COV, and SR. Models with different numbers of groups, ranging from one to eight, were evaluated based on various fit indices, while attempts to estimate more than nine groups failed to converge. To identify the optimal model, we examined several fit indices, including AIC, BIC, SABIC, entropy, and BLRT. Among these, the three-group model was the best fit, as it had the lowest AIC, BIC, and SABIC values (Weller et al., 2020). Additionally, the entropy and BLRT *p*-value were considered to further validate model selection. High entropy values for the two-group and three-group models suggested good separation between the groups (Celeux & Soromenho, 1996). Moreover, the BLRT *p*-value was below zero point zero for both models, indicating significantly better model fit compared to alternative solutions (Table 5). Overall, the three-profile solution was determined to be the best fit, as it demonstrated the lowest AIC, BIC, and SABIC values, along with strong entropy and BLRT p-values, confirming its superior fit over other models.

Table 5
Comparison of the Fit Models with Different Group Numbers

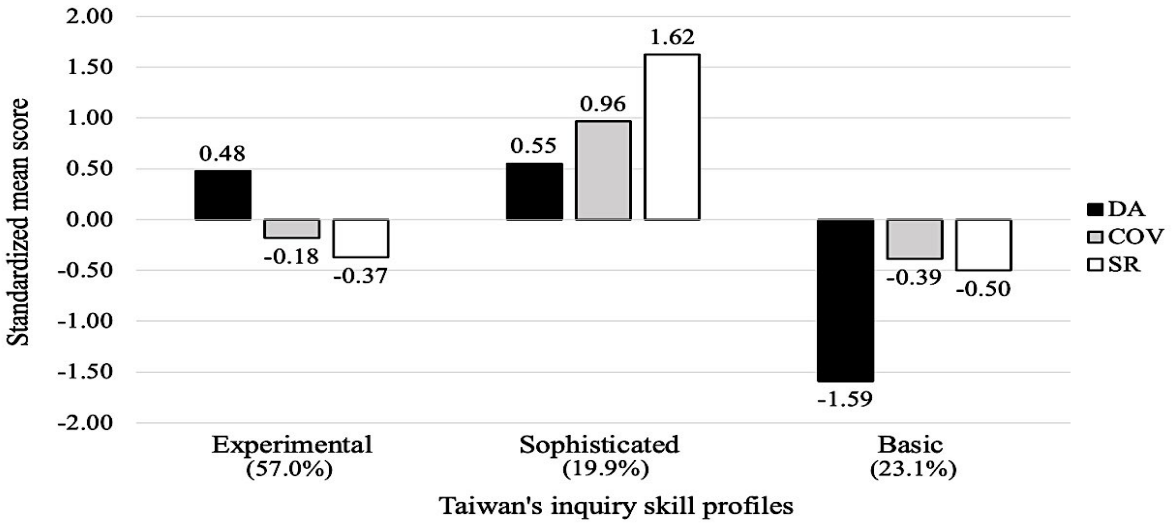
Indicators	1 group	2 group	3 group	4 group	5 group	6 group	7 group	8 group
Log-likelihood	-2828.8	-2594.1	-2435.4	-2434.9	-2411.4	-2080.0	-2418.7	-1904.1
AIC	5669.7	5208.2	4898.8	4905.8	4866.8	4212.0	4897.3	3876.3
BIC	5696.7	5253.3	4961.9	4986.9	4965.9	4329.0	5032.4	4029.4
SABIC	5677.6	5221.5	4917.4	4929.7	4896.0	4246.5	4937.2	3921.4
Entropy	1.00	.98	.93	.81	.83	.86	.66	.72
BLRT (p)	NA	.0099	.0099	.6931	.0099	.0099	.7525	.0099
Smallest group frequency	1.00	0.23	0.20	0.03	0.03	0	0	0

Based on the outcomes of the LPA, we characterized three distinct profiles, labeled as "Experimental," "Sophisticated," and "Basic." The Experimental profile (57.0%) comprised the largest number of students. The Sophisticated profile and Basic profile accounted for 19.9% and 23.1%, respectively. Figure 8 highlights the distinguishable nature of these profiles based on their inquiry skills. The Sophisticated profile demonstrated strong proficiency across SR, DA, and COV skills. The Experimental profile excelled primarily in DA, with moderate proficiency in COV and SR skills. Conversely, the Basic profile exhibited standardized mean scores below average across all three skills, indicating deficiencies in their performance.

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

Figure 8
Taiwanese High School Students' Inquiry Skill Profiles



The Association Between Inquiry Profiles and Scientific Competency

One-way ANOVA was conducted to examine variations in scientific competency achievement among different profiles of students. Additionally, a $\chi 2$ test and cross-table analysis were utilized to evaluate the presence of significant associations between students' background factors, such as gender, major, parents' education level, and family financial situation. A descriptive analysis of the scientific competency scores for each profile is summarized in Table 6. The results demonstrate distinct performance levels across the profiles. The Sophisticated profile exhibited the highest average score (M = 18.44, SD = 4.91), demonstrating their advanced level of scientific competency. The Experimental profile ranked second with a moderately high average score (M = 16.06, SD = 5.59), while the Basic profile had the lowest average score (M = 13.23, SD = 6.55), indicating the greatest need for development.

Table 6
Description of Scientific Competency Test Scores of Different Profiles

Profile	*n*	*M*	*SD*	*Min*	*Max*
Experimental	380	16.06	5.59	0	30
Sophisticated	133	18.44	4.91	0	30
Basic	154	13.23	6.55	0	30

The one-way ANOVA analysis indicates significant differences in scientific competency test scores among different profiles, with a moderate effect size (F (2, 664) = 30.20, p < .001, partial η^2 = .083), as shown in Table 7. These results suggest that students categorized as 'Experimental,' 'Sophisticated,' and 'Basic' performed differently on the scientific competency test. Post hoc Bonferroni tests further revealed statistically significant differences in test scores (p < .001), with moderate and large effect sizes. Specifically, the Bonferroni tests identified significant mean differences between each pair of profiles. In summary, students classified as the Sophisticated profile demonstrated higher scientific competency than both the Experimental profile and the Basic profile, while the Experimental profile performed better than the Basic.

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

Table 7
The Result of Post Hoc Bonferroni Tests of Different Profiles

Comparison		*M* difference	*SE*	*p*	*d*
Condition	**Condition**				
Sophisticated	- Experimental	2.378	0.575	< .001	.436
	- Basic	5.209	0.675	< .001	.895
Experimental	- Basic	2.831	0.545	< .001	.478

Table 8 presents the results of chi-square tests examining the association between students' background factors and their scientific inquiry skill profiles. The analysis shows no significant differences in the distribution of students' gender ($\chi^2 = 1.122$, $p = .571$), parents' education level ($\chi^2 = 15.490$, $p = .345$), and family financial situation ($\chi^2 = 1.749$, $p = .417$). However, a significant difference was found in the distribution of students' majors ($\chi^2 = 23.078$, $p < .001$), indicating that students' majors significantly influence their scientific inquiry skill profiles.

Table 8
Chi-Square Tests of Students' Background Factor

Background factor	χ^2	*p*
Gender	1.122	.571
Major	23.078	< .001
Parents' education level	15.490	.345
Family financial situation	1.749	.417

The distribution of inquiry skill profiles varies significantly between students majoring in social and natural sciences. Among social science majors ($n = 187$), 50.3% (94 students) are classified as Experimental profile, 14.4% (27 students) as Sophisticated, and 35.3% (66 students) as Basic. In contrast, for natural science majors ($n = 440$), 60.0% (264 students) are Experimental, 22.0% (97 students) are Sophisticated, and 18.0% (79 students) are Basic. A Pearson chi-square residual analysis revealed notable differences between these groups (Agresti, 2019). Follow-up tests indicated that the proportion of Experimental profile and Sophisticated among natural science majors is significantly higher than among social science majors, with standardized residuals of 2.25 and 2.19, respectively. Conversely, the proportion of Basic is significantly lower for natural science majors compared to social science majors (standardized residual = -4.71). Interestingly, across both groups, the Experimental profile represents over half of the students, suggesting that many possess basic data analysis skills. However, the proportion of Sophisticated, who exhibit advanced inquiry and reasoning capabilities, remains relatively low in both majors.

Discussion

Inquiry Skill Profile Model

This study identified three distinct inquiry skill profiles among Taiwanese high school students, highlighting variations in their proficiency across SR, DA, and COV. These profiles provide empirical support for partially replicating student classifications based on inquiry abilities. From a statistical modeling perspective, selecting $n = 3$ as the optimal solution is supported by multiple factors. First, BIC and SABIC values show a notable decrease at $n = 3$, whereas further increasing the number of profiles results in only marginal improvements. Second, the BLRT ceases to be significant beyond $n = 3$, indicating that additional profiles do not contribute significantly to the model. Third, the three-profile solution ensures an adequate sample distribution, preventing the formation of excessively small classes that may compromise statistical power. Finally, the $n = 3$ model aligns with theoretical and practical interpretability, preventing excessive complexity that could hinder meaningful application.

From a theoretical perspective, this decision is grounded in the e data-covariation and mechanistic causal reasoning framework (Bao et al., 2022), which underscores the role of DA in identifying covariation patterns and validating

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

evidence for mechanistic causal relationships. Within this three-profile model, the Sophisticated group demonstrates strong DA abilities alongside high levels of COV and SR. In contrast, the Basic group exhibits weaker DA skills, with the lowest average performance in COV and SR. Additionally, Nkwanyana et al. (2023) highlighted that some students struggle to translate data analysis into meaningful insights, aligning with the Experimental group, which demonstrates moderate DA proficiency but suboptimal performance in COV and SR. As a result, the three-profile solution is both statistically and theoretically well-supported, offering an optimal balance between model fit, sample distribution, and interpretability.

Although the three-profile model identified in this study—Sophisticated, Experimental, and Basic—differs from the four-profile model proposed in China (Sui et al., 2024), the core characteristics of these profiles remain highly consistent across both contexts. In both models, the Sophisticated profile exhibits high proficiency across all inquiry skills, while the Basic profile reflects notable deficiencies. The Experimental profile identified in Taiwan closely aligns with China's Experimental and Moderate profiles, suggesting similar distributions of inquiry skills despite minor differences in classification.

From a model simplicity perspective, the three-profile solution effectively captures essential variations in students' inquiry abilities while maintaining clarity and usability. This streamlined framework reinforces the robustness and generalizability of inquiry skill profiling, demonstrating its adaptability across different educational settings. By validating and extending the inquiry skill profile model, this study enhances our understanding of students' scientific competencies and provides valuable insights for designing targeted interventions to improve inquiry skills in science education.

Students' Scientific Competency and Background Factors

The findings indicate that students classified within the Sophisticated profile exhibit the highest levels of scientific competency, significantly outperforming those in the Experimental and Basic profiles. This supports the notion that reasoning abilities are central to scientific competency (Bao et al., 2022) and play a crucial role in science learning (Coletta & Phillips, 2005). Reasoning skills have consistently been identified as essential for problem-solving and scientific inquiry, with research linking these skills to higher academic achievement in science (Alshamali & Daher, 2016). Moreover, scientific reasoning functions both as a cognitive skill and as a domain of knowledge, contributing to scientific competency and improved educational outcomes (Pasigon, 2024; Zimmerman, 2007). The exceptional performance of students in the Sophisticated profile underscores the importance of advanced reasoning capabilities in interpreting, synthesizing, and applying scientific concepts, aligning with prior research emphasizing these skills as critical for science education. Conversely, the lower reasoning proficiency observed in students within the Experimental and Basic profiles is closely associated with their reduced scientific competency. Adey and Shayer (1993) highlighted that developing science process skills has a lasting impact on learning, further underscoring the critical role of reasoning in educational outcomes. These findings emphasize the necessity of targeted interventions to strengthen reasoning skills, particularly for students in lower-performing groups, as a strategy to enhance scientific understanding and improve academic performance.

The findings also suggest that curricular design should be sensitive to students' academic focus, given the significant association between students' majors and their inquiry skill profiles. Students majoring in social sciences, who were more frequently classified as Basic, may require additional support to enhance their inquiry skills and bridge the gap with their natural science peers. To address this disparity, curriculum elements could be tailored to align with their academic background, for example, by integrating scientific inquiry within social science contexts, making these skills more relevant and accessible. Research suggests that students are more likely to retain and apply knowledge when it is taught in contexts that are meaningful and engaging (Iran-Nejad et al., 1990).

Furthermore, research by Russell and French (2002) indicated that nonscience majors often hold negative attitudes toward science, but experiential learning strategies can effectively overcome these barriers. By incorporating hands-on, inquiry-driven learning approaches, educators can create more engaging and meaningful science education experiences, ultimately improving inquiry skills among social science students.

Moreover, students majoring in natural sciences were more likely to be categorized as Experimental or Sophisticated, whereas those in social sciences were predominantly classified as Basic. This suggests that scientific inquiry skills may play a critical role in influencing students' academic choices. Students with stronger inquiry skills or those more inclined toward higher-level inquiry processes may gravitate toward natural science tracks, whereas those with less-developed inquiry skills may prefer social sciences.

This finding raises important considerations for science education policy. If students' inquiry skills significantly influence their academic pathways, early interventions that develop these skills could expand students' access to

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

science-related disciplines. For instance, targeted support for students in the Basic profile could help mitigate skill-related barriers that deter some students from pursuing natural sciences. Additionally, the low proportion of students classified as Sophisticated across both groups highlights the need for enhancing advanced reasoning abilities across disciplines. These skills are essential for scientific competency and interdisciplinary problem-solving, reinforcing the importance of strengthening higher-order thinking skills within the broader education system.

There was no significant association between students' inquiry skill profiles and background factors such as gender, parental education level, or family financial status. This lack of association suggests that scientific inquiry skills may be relatively independent of these socioeconomic variables, indirectly supporting the effectiveness of Taiwan's science education system in promoting equity. The consistent performance patterns across different inquiry skill profiles indicate that Taiwan's education system not only delivers quality science education but also ensures equitable learning opportunities for students from diverse backgrounds.

However, caution is warranted in interpreting these findings. Studies examining multi-level moderation or mediation effects, or conducting subgroup analyses, often require large-scale datasets—such as those used in international assessments like PISA or TIMSS—to accurately detect subtle differences. To better understand the nuanced and context-dependent effects of socioeconomic status on learning outcomes, future research should consider larger and more diverse samples (Tan, 2024).

The implications are profound for education, particularly in tailoring instructional strategies to meet the diverse needs of students. By recognizing the three distinct inquiry skill profiles—Basic, Experimental, and Sophisticated—educators can design targeted interventions that address the specific needs of each group, ultimately enhancing overall educational outcomes.

Students in the Basic profile, who frequently struggle with science learning, would benefit from instructional interventions focused on building foundational skills and enhancing engagement. Glynn et al. (2007) suggested that linking science concepts to career pathways for nonscience majors can increase both engagement and achievement. This approach could involve strategically integrating real-world applications and experiential learning to make scientific inquiry more accessible. By increasing students' interest and confidence in science, their DA skills may improve, leading to enhancements in COV and SR abilities.

On the other hand, research by Kuhn (2007) highlighted that reasoning processes can be applied across multiple domains. Students in the Experimental profile, who generally exhibit strong analytical skills but may require further development in scientific reasoning, could benefit from more advanced inquiry-based tasks. Kind and Osborne (2017) propose that scientific reasoning varies based on both content knowledge and epistemic understanding. For these students, interventions could include complex problem-solving tasks or higher-order thinking exercises, bridging the gap between their current skill set and the advanced reasoning abilities required for scientific competency.

Limitation

This study has certain limitations in its data collection process. Although data were gathered from 667 students, the sample was restricted to a single high school in central Taiwan. Despite this limitation, the resulting model closely aligns with prior research, suggesting that the sampling approach is valid and that the findings are reliable. However, students from other regions in Taiwan or different cultural and educational contexts may exhibit variations in their inquiry skill profiles. While the observed similarities between Taiwanese and Chinese high school students indicate a degree of universality in inquiry skill classifications, additional research is needed to examine the applicability of these profiles across diverse cultural and educational settings. Such investigations would provide further validation of the universality of scientific education principles and offer deeper insights into how inquiry skill development is influenced by contextual factors.

While this study did not identify significant relationships between students' inquiry skill profiles and background factors such as gender, parental education level, and family financial status, this absence of statistical significance should not be interpreted as definitive evidence of no effect. Instead, it may reflect methodological constraints, including sample size limitations and measurement sensitivity. Additionally, the background variables in this study were broadly categorized (e.g., binary classifications of parental education level and financial status), which may not fully capture subtle socio-economic disparities that influence inquiry skills.

Future research could adopt more granular socio-economic indicators to gain a deeper understanding of how socio-economic factors shape inquiry skill development. Potential avenues for investigation include access to scientific learning resources at home, parental involvement in science education, and school-level contextual factors. A more comprehensive examination of these variables could provide richer insights into the relationship between socio-

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

economic background and scientific inquiry skills, ultimately informing policy decisions and instructional interventions aimed at bridging educational gaps.

Conclusions and Implications

Scientific inquiry skills are essential indicators of students' cognitive abilities and their readiness to engage in scientific reasoning. This study successfully replicated and validated the inquiry skill profile model from previous research, confirming its robustness across different educational settings. Through LPA, we identified three distinct inquiry skill profiles—Sophisticated, Experimental, and Basic—each characterized by varying levels of proficiency in DA, COV, and SR. These findings provide empirical evidence that students' inquiry skills are not uniformly distributed, but rather follow distinct patterns based on their competencies in scientific inquiry.

Furthermore, this study established a significant correlation between students' inquiry skill profiles and their scientific competency. Students classified under the Sophisticated profile demonstrated higher scientific competency, significantly outperforming those in the Experimental and Basic profiles. These results emphasize the critical role of advanced reasoning abilities in enhancing students' understanding and application of scientific concepts. Conversely, students in the Basic profile exhibited the lowest levels of scientific competency, underscoring the need for targeted interventions to improve their inquiry skills.

Notably, demographic factors such as gender, parental education level, and family financial status did not significantly impact students' inquiry skill profiles, reinforcing the effectiveness of Taiwan's science education system in providing equitable learning opportunities. However, academic majors exhibited a strong association with inquiry skill profiles, with natural science majors demonstrating higher inquiry skill proficiency than their social science counterparts. This finding suggests that scientific inquiry skills may influence students' academic choices and highlights the importance of science curricula that support students across different disciplines.

Acknowledgements

This work was financially supported by the National Science and Technology Council of Taiwan under contracts the NSTC 114-2410-H-003-027-MY3, the NSTC 114-2423-H-003-005, the NSTC 113-2410-H-003-034-MY3, the NSTC 114-2410-H-656-013-MY3 and the "Institute for Research Excellence in Learning Sciences" of National Taiwan Normal University (NTNU) from The Featured Areas Research Center Program within the framework of the Higher Education Sprout Project by the Ministry of Education (MOE) in Taiwan.

Declaration of Generative AI and AI-assisted Technologies

During the preparation of this work, the authors used ChatGPT in order to help with some stylistic issues and translation. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

Abd-El-Khalick, F., BouJaoude, S., Duschl, R., Lederman, N. G., Mamlok-Naaman, R., Hofstein, A., Niaz, M., Treagust, D., & Tuan, H.-l. (2004). Inquiry in science education: International perspectives. *Science Education*, *88*(3), 397–419. https://doi.org/10.1002/sce.10118

Adey, P., & Shayer, M. (1993). An exploration of long-term far-transfer effects following an extended intervention program in the high school science curriculum. *Cognition and Instruction*, *11*(1), 1–29. https://doi.org/10.1207/s1532690xci1101_1

Agresti, A. (2012). *Categorical data analysis* (Vol. 792). John Wiley & Sons. https://doi.org/10.1002/0471249688

Alshamali, M. A., & Daher, W. M. (2016). Scientific reasoning and its relationship with problem solving: the case of upper primary science teachers. *International Journal of Science and Mathematics Education*, *14*(6), 1003–1019. https://doi.org/10.1007/s10763-015-9646-1

Bao, L., Cai, T., Koenig, K., Fang, K., Han, J., Wang, J., Liu, Q., Ding, L., Cui, L., Luo, Y., Wang, Y., Li, L., & Wu, N. (2009). Learning and scientific reasoning. *Science*, *323*(5914), 586–587. https://doi.org/10.1126/science.1167740

Bao, L., & Koenig, K. (2019). Physics education research for 21st century learning. *Disciplinary and Interdisciplinary Science Education Research*, *1*(1), 2. https://doi.org/10.1186/s43031-019-0007-8

Bao, L., Koenig, K., Xiao, Y., Fritchman, J., Zhou, S., & Chen, C. (2022). Theoretical model and quantitative assessment of scientific thinking and reasoning. *Physical Review Physics Education Research*, *18*(1), Article 010115. https://doi.org/10.1103/PhysRevPhysEducRes.18.010115

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

Bell, T., Urhahne, D., Schanze, S., & Ploetzner, R. (2010). Collaborative inquiry learning: Models, tools, and challenges. *International Journal of Science Education*, *32*(3), 349–377. https://doi.org/10.1080/09500690802582241

Bergman, L. R., & Trost, K. (2006). The person-oriented versus the variable-oriented approach: Are they complementary, opposites, or exploring different worlds? *Merrill-Palmer Quarterly*, *52*(3), 601–632. http://www.jstor.org/stable/23096208

Beswick, K. (2021). Inquiry-based approaches to mathematics learning, teaching, and mathematics education research. *Journal of Mathematics Teacher Education*, *24*(2), 123–126. https://doi.org/10.1007/s10857-021-09494-4

Bowers, A. J., Sprott, R., & Taff, S. A. (2013). Do we know who will drop out?: A review of the predictors of dropping out of high school: Precision, sensitivity, and specificity. *The High School Journal*, *96*(2), 77–100.

Bryant, P., Nunes, T., Hillier, J., Gilroy, C., & Barros, R. (2015). The importance of being able to deal with variables in learning science. *International Journal of Science and Mathematics Education*, *13*(1), 145–163. https://doi.org/10.1007/s10763-013-9469-x

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of Classification*, *13*(2), 195–212. https://doi.org/10.1007/BF01246098

Chang, C.-Y., & Cheng, W.-Y. (2008). Science achievement and students' self-confidence and interest in science: A Taiwanese representative sample study. *International Journal of Science Education*, *30*(9), 1183–1200. https://doi.org/10.1080/09500690701435384

Chen, H.-C., Gijlers, H., Sui, C.-J., & Chang, C.-Y. (2023). Asian students' cultural orientation and computer self-efficacy significantly related to online inquiry-based learning outcomes on the go-lab platform. *Journal of Science Education and Technology*, *32*(5), 743–758. https://doi.org/10.1007/s10956-023-10058-9

Chen, Z., & Klahr, D. (1999). All other things being equal: Acquisition and transfer of the control of variables strategy. *Child Development*, *70*(5), 1098–1120. https://doi.org/10.1111/1467-8624.00081

Clark, S. (2009). *Relating latent class analysis results to variables not included in the analysis*. University of California.

Coletta, V. P., & Phillips, J. A. (2005). Interpreting FCI scores: Normalized gain, preinstruction scores, and scientific reasoning ability. *American journal of physics*, *73*(12), 1172–1182. https://doi.org/10.1119/1.2117109

Collins, L. M., & Lanza, S. T. (2009). *Latent class and latent transition analysis: With applications in the social, behavioral, and health sciences* (Vol. 718). John Wiley & Sons. https://doi.org/10.1002/9780470567333

Gabriel, A. S., Daniels, M. A., Diefendorff, J. M., & Greguras, G. J. (2015). Emotional labor actors: A latent profile analysis of emotional labor strategies. *Journal of Applied Psychology*, *100*(3), 863–879. https://doi.org/10.1037/a0037408

Gagné, R. M. (1963). The learning requirements for enquiry. *Journal of Research in Science Teaching*, *1*(2), 144–153. https://doi.org/10.1002/tea.3660010211

Galano, S., Palazzo, L., & Testa, I. (2024). A latent profile analysis of students' attitudes towards astronomy across grades 9–13. *International Journal of Science Education*, *46*(14), 1480–1516. https://doi.org/10.1080/09500693.2023.2289485

Gandomi, A., & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, *35*(2), 137–144. https://doi.org/10.1016/j.ijinfomgt.2014.10.007

Gibson, H. L., & Chase, C. (2002). Longitudinal impact of an inquiry-based science program on middle school students' attitudes toward science. *Science Education*, *86*(5), 693–705. https://doi.org/10.1002/sce.10039

Glynn, S. M., Taasoobshirazi, G., & Brickman, P. (2007). Nonscience majors learning science: A theoretical model of motivation. *Journal of Research in Science Teaching*, *44*(8), 1088–1107. https://doi.org/10.1002/tea.20181

Goodman, L. A. (2002). Latent Class Analysis: The Empirical Study of Latent Types, Latent Variables, and Latent Structures. In J. A. Hagenaars & A. L. McCutcheon (Eds.), *Applied Latent Class Analysis* (pp. 3–55). chapter, Cambridge: Cambridge University Press.

Hedges, L. V. (2018). Challenges in building usable knowledge in education. *Journal of Research on Educational Effectiveness*, *11*(1), 1–21. https://doi.org/10.1080/19345747.2017.1375583

Hirschi, A., & Valero, D. (2017). Chance events and career decidedness: Latent profiles in relation to work motivation. *The Career Development Quarterly*, *65*(1), 2–15. https://doi.org/10.1002/cdq.12076

Howard, M. C., & Hoffman, M. E. (2018). Variable-centered, person-centered, and person-specific approaches: Where theory meets the method. *Organizational Research Methods*, *21*(4), 846–876. https://doi.org/10.1177/1094428117744021

Husbye, N., & Dorner, L. M. (2017). Teaching strategies to develop inquiry and literacy skills: languaging in foreign language immersion education. *L2 Journal: An Open Access Refereed Journal for World Language Educators*, *9*(1). https://doi.org/10.5070/L29128532

Iran-Nejad, A., McKeachie, W. J., & Berliner, D. C. (1990). The multisource nature of learning: an introduction. *Review of Educational Research*, *60*(4), 509–515. https://doi.org/10.3102/00346543060004509

Kampa, N., Neumann, I., Heitmann, P., & Kremer, K. (2016). Epistemological beliefs in science—a person-centered approach to investigate high school students' profiles. *Contemporary Educational Psychology*, *46*, 81–93. https://doi.org/10.1016/j.cedpsych.2016.04.007

Kind, P., & Osborne, J. (2017). Styles of scientific reasoning: A cultural rationale for science education? *Science Education*, *101*(1), 8–31. https://doi.org/10.1002/sce.21251

Koenig, K., Wood, K. E., Bortner, L. J., & Bao, L. (2019). Modifying traditional labs to target scientific reasoning. *Journal of College Science Teaching*, *48*(5), 28–35. https://www.jstor.org/stable/26901313

Kuhn, D. (2007). Reasoning about multiple variables: Control of variables is not the only challenge. *Science Education*, *91*(5), 710–726. https://doi.org/10.1002/sce.20214

Kuhn, D., & Pease, M. (2008). What needs to develop in the development of inquiry skills? *Cognition and Instruction*, *26*(4), 512–559. https://doi.org/10.1080/07370000802391745

Li, W. C., Nichanian, A., Lin, J., & Braithwaite, G. (2023). Investigating the impacts of COVID-19 on aviation safety based on occurrences captured through flight data monitoring. *Ergonomics*, *66*(10), 1534–1548. https://doi.org/10.1080/00140139.2022.2155317

Lin, C.-L. S., & Chang, C.-Y. (2017). Personality and family context in explaining grit of Taiwanese high school students. *Eurasia journal of mathematics, science and technology education*, *13*(6), 2197–2213. https://doi.org/10.12973/eurasia.2017.01221a

Lipman, M. (2003). *Thinking in education* (Vol. 304). Cambridge University Press.

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

Lohman, D. F., & Lakin, J. M. (2011). Intelligence and reasoning. *The Cambridge handbook of intelligence*, 419–441.
Makel, M. C., Smith, K. N., McBee, M. T., Peters, S. J., & Miller, E. M. (2019). A Path to greater credibility: Large-Scale collaborative education research. *AERA Open*, *5*(4), Article 2332858419891963. https://doi.org/10.1177/2332858419891963
Minner, D. D., Levy, A. J., & Century, J. (2010). Inquiry-based science instruction—what is it and does it matter? Results from a research synthesis years 1984 to 2002. *Journal of Research in Science Teaching*, *47*(4), 474–496. https://doi.org/10.1002/tea.20347
Morgan, G. B. (2015). Mixed mode latent class analysis: An examination of fit index performance for classification. *Structural Equation Modeling: A Multidisciplinary Journal*, *22*(1), 76–86. https://doi.org/10.1080/10705511.2014.935751
Morris, D. L. (2025). Rethinking science education practices: shifting from investigation-centric to comprehensive inquiry-based instruction. *Education Sciences*, *15*(1), Article 73. https://doi.org/10.3390/educsci15010073
Morrison, K. (2022). Conceptual replications, research, and the "what works" agenda in education. *Educational Research and Evaluation*, *27*(1-2), 35–60. https://doi.org/10.1080/13803611.2021.2022314
Mullis, I. V. S., & Martin, M. O. (2013). *TIMSS 2015 Assessment Frameworks*.
National Research Council. (1996). *National science education standards*. The National Academies Press. https://doi.org/10.17226/4962
National Research Council. (2000). *Inquiry and the National science education standards: A guide for teaching and learning*. The National Academies Press. https://doi.org/10.17226/9596
Nkwanyana, A., Mathews, V., Zachary, I., & Bhayani, V. (2023). Skills and competencies in health data analytics for health professionals: a scoping review protocol. *BMJ Open*, *13*(11), Article e070596. https://doi.org/10.1136/bmjopen-2022-070596
Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A Monte Carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396
OECD. (2017). *PISA 2015 assessment and analytical framework: Science, reading, mathematics, financial literacy and collaborative problem solving*. OECD Publishing. https://doi.org/10.1787/9789264281820-en
Omarchevska, Y., Lachner, A., Richter, J., & Scheiter, K. (2022). Do video modeling and metacognitive prompts improve self-regulated scientific inquiry? *Educational Psychology Review*, *34*(2), 1025–1061. https://doi.org/10.1007/s10648-021-09652-3
Papadakis, S. (2022). Apps to promote computational thinking and coding skills to young age children: A pedagogical challenge for the 21st century learners. *Educational Process: International Journal (EDUPIJ)*, *11*(1), 7–13.
Papadakis, S., Kiv, A. E., Kravtsov, H. M., Osadchyi, V. V., Marienko, M. V., Pinchuk, O. P., Shyshkina, M. P., Sokolyuk, O. M., Vakaliuk, T. A., & Azarova, L. E. (2023). Unlocking the power of synergy: the joint force of cloud technologies and augmented reality in education. Joint Proceedings of the 0th Workshop on Cloud Technologies in Education (CTE 2021) and 5th International Workshop on Augmented Reality in Education (AREdu 2022), Kryvyi Rih, Ukraine, May 23, 2022.
Papadakis, S., Kravtsov, H. M., Osadchyi, V. V., Marienko, M. V., Pinchuk, O. P., Shyshkina, M. P., Sokolyuk, O. M., Vakaliuk, T. A., & Striuk, A. M. (2023). Revolutionizing education: using computer simulation and cloud-based smart technology to facilitate successful open learning. In *Joint proceedings of the 10th Illia O. Teplytskyi Workshop on Computer Simulation in Education and Workshop on Cloud-based Smart Technologies for Open Education (CoSinEi and CSTOE 2022) co-located with ACNS Conference on Cloud and Immersive Technologies* (pp. 1-13). https://ceur-ws.org
Pasigon, C. P. (2024). Mathematical Proficiency, Scientific Reasoning, Metacognitive Skills, and Performance of Learners in Physics: A Mathematical Model. *International Journal of Learning, Teaching and Educational Research*, *23*(4), 252–278.
Pedaste, M., Mäeots, M., Siiman, L. A., de Jong, T., van Riesen, S. A. N., Kamp, E. T., Manoli, C. C., Zacharia, Z. C., & Tsourlidaki, E. (2015). Phases of inquiry-based learning: Definitions and the inquiry cycle. *Educational Research Review*, *14*, 47–61. https://doi.org/10.1016/j.edurev.2015.02.003
Perry, T., Morris, R., & Lea, R. (2022). A decade of replication study in education? A mapping review (2011–2020). *Educational Research and Evaluation*, *27*(1-2), 12–34. https://doi.org/10.1080/13803611.2021.2022315
Rosenberg, J. M., Beymer, P. N., Anderson, D. J., Van Lissa, C., & Schmidt, J. A. (2019). tidyLPA: An R package to easily carry out latent profile analysis (LPA) using open-source or commercial software. *Journal of Open Source Software*, *3*(30), 978.
Russell, C. P., & French, D. P. (2002). Factors affecting participation in traditional and inquiry-based laboratories. *Journal of College Science Teaching*, *31*(4), 225–229. https://www.proquest.com/scholarly-journals/factors-affecting-participation-traditional/docview/200317377/se-2?accountid=45566
Shaw, V. F. (1996). The Cognitive Processes in Informal Reasoning. *Thinking & Reasoning*, *2*(1), 51–80. https://doi.org/10.1080/135467896394564
Snodgrass Rangel, V., Vaval, L., & Bowers, A. (2020). Investigating underrepresented and first-generation college students' science and math motivational beliefs: A nationally representative study using latent profile analysis. *Science Education*, *104*(6), 1041–1070. https://doi.org/10.1002/sce.21593
Spurk, D., Hirschi, A., Wang, M., Valero, D., & Kauffeld, S. (2020). Latent profile analysis: A review and "how to" guide of its application within vocational behavior research. *Journal of Vocational Behavior*, *120*, 103445. https://doi.org/10.1016/j.jvb.2020.103445
Strand-Cary, M., & Klahr, D. (2008). Developing elementary science skills: Instructional effectiveness and path independence. *Cognitive Development*, *23*(4), 488–511. https://doi.org/10.1016/j.cogdev.2008.09.005
Sui, C.-J., Chen, H.-C., Cheng, P.-H., & Chang, C.-Y. (2023). The Go-Lab platform, an inquiry-learning space: investigation into students' technology acceptance, knowledge integration, and learning outcomes. *Journal of Science Education and Technology*, *32*(1), 61–77. https://doi.org/10.1007/s10956-022-10008-x
Sui, C.-J., Hsiao, S.-Y., Yeh, S.-C., Zhao, P., Chang, C.-Y., & Lin, J. (2024). Do they have inquiry skill profiles? Exploring high school students' scientific inquiry in an animation-based activity. *Science Education*, *108*, 467–494. https://doi.org/10.1002/sce.21844
Tan, C. Y. (2024). Socioeconomic Status and Student Learning: Insights from an umbrella review. *Educational Psychology Review*, *36*(4), 100. https://doi.org/10.1007/s10648-024-09929-3

https://doi.org/10.33225/jbse/25.24.824

ISSN 1648–3898 /Print/
ISSN 2538–7138 /Online/

Tschirgi, J. E. (1980). Sensible reasoning: A hypothesis about hypotheses. *Child Development*, *51*(1), 1–10. https://doi.org/10.2307/1129583
Vermunt, J. K. (2002). *Latent class cluster analysis*. *Applied latent class analysis.* Cambridge UniversityPress.
Wang, M., & Hanges, P. J. (2011). Latent class procedures: Applications to organizational research. *Organizational Research Methods*, *14*(1), 24–31. https://doi.org/10.1177/1094428110383988
Weller, B. E., Bowen, N. K., & Faubert, S. J. (2020). Latent class analysis: A guide to best practice. *Journal of Black Psychology*, *46*(4), 287–311. https://doi.org/10.1177/0095798420930932
Windschitl, M. (2003). Inquiry projects in science teacher education: What can investigative experiences reveal about teacher thinking and eventual classroom practice? *Science Education*, *87*(1), 112–143. https://doi.org/10.1002/sce.10044
Woo, S. E., Jebb, A. T., Tay, L., & Parrigon, S. (2018). Putting the "person" in the center: Review and synthesis of person-centered approaches and methods in organizational science. *Organizational Research Methods*, *21*(4), 814–845. https://doi.org/10.1177/1094428117752467
Wu, H.-K., & Shah, P. (2004). Exploring visuospatial thinking in chemistry learning. *Science Education*, *88*(3), 465–492. https://doi.org/10.1002/sce.10126
Wu, H. K., & Hsieh, C. E. (2007). Developing sixth graders' inquiry skills to construct explanations in inquiry-based learning environments. *International Journal of Science Education*, *28*(11), 1289–1313. https://doi.org/10.1080/09500690600621035
Yang, K.-L., & Lin, F.-L. (2015). The effects of PISA in Taiwan: Contemporary assessment reform. In K. Stacey & R. Turner (Eds.), *Assessing Mathematical Literacy: The PISA Experience* (pp. 261–273). Springer International Publishing. https://doi.org/10.1007/978-3-319-10121-7_14
Zhou, S., Han, J., Koenig, K., Raplinger, A., Pi, Y., Li, D., Xiao, H., Fu, Z., & Bao, L. (2016). Assessment of scientific reasoning: the effects of task context, data, and design on student reasoning in control of variables. *Thinking Skills and Creativity*, *19*, 175–187. https://doi.org/10.1016/j.tsc.2015.11.004
Zimmerman, C. (2007). The development of scientific thinking skills in elementary and middle school. *Developmental Review*, *27*(2), 172–223. https://doi.org/10.1016/j.dr.2006.12.001

Received: *February 07, 2025* Revised: *March 26, 2025* Accepted: *August 10, 2025*

Cite as: Chen, Y.-C., Sui, C.-J., & Chang, C.-Y. (2025). Profiling scientific inquiry skills: Exploring relationships with scientific competency and background factors in high school students. *Journal of Baltic Science Education*, *24*(5), 824–842. https://doi.org/10.33225/jbse/25.24.824

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