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Improving Critical Thinking through AI-Supported Socio-Scientific Issues Instruction

Qin Liu [1], Chia Ching Tu[2]

International College, Krirk University, Bangkok, Thailand, 10220
tulisa0929@gmail.com (Corresponding author)

Abstract. This study developed and evaluated a personalized socio-scientific issues (SSIs) education model based on artificial intelligence (AI) adaptive learning environments with the goal to improve critical thinking skills among college students in China. A quasi-experimental pre/post-test design was used with 101 geology majors, allocating 52 to the experimental group receiving AI-supported SSIs instructions and 49 to the control group receiving regular instructions. The California Critical Thinking Disposition Inventory and California Critical Thinking Skills Test were used to measure critical thinking dispositions and skills. The results of analyses of covariance showed that the AI-supported SSI model led to significant increases in critical thinking dispositions ($p < 0.01$) and skills ($p < 0.01$) compared to the control. The findings suggest that AI-enhanced personalized SSI education models have the potential to improve critical thinking outcomes for 21st century learning. Further research with larger and more diverse samples is needed to replicate effects.

Keywords: Socio-scientific issues, Artificial intelligence, Adaptive learning environment, Critical thinking.

1. Introduction

Globalization and the technological revolution of the 21st century have shaped a flattened educational world, where emphasis is increasingly placed on the development and enhancement of 21st century skills (Friedman, 2005). The American Education Association (2002) reported that among 21st century skills, the four Cs (i.e., critical thinking, communication, collaboration, and creativity) are important for the development of present and future society. Through research and modeling, Guo (2016) described the relationship between the four Cs as follows: critical thinking can gradually evolve into creative thinking, driven by communication and collaboration, so that critical thinking can be said to be a foundational competency of the four Cs. Critical thinking is a major component of scientific literacy and an essential higher-order mindset in many professions (Murcia, 2007); therefore, improving critical thinking is extremely important for college students who are about to enter society.

Multiple studies have indicated that socio-scientific issues education can enhance the four Cs of critical thinking (He, 2016), communication (Chung, Yoo, Kim, Lee, & Zeidler, 2016), collaboration (Jin & Wu, 2017), and creativity (Huang, 1999). Critical thinking is a foundational competency of the four Cs, but currently, no personalized, adjustable model for socio-scientific issues education exists. Artificial intelligence (AI) plays an important role in the building of personalized and adjustable adaptive learning environments. Therefore, in this paper, a socio-scientific issues education framework is designed with the goal to enhance the critical thinking of science and engineering students.

AI plays a crucial role in advancing society, economy, and education. It is a vital technology for the construction of adaptive learning systems (Chassignol, Khoroshavin, Klimova, & Bilyatdinova, 2018). Its intelligent and personalized features effectively enhance the experiences of learners and improve learning outcomes (Chen, Chen, & Lin, 2020). The Information Technology in Higher Education Association of the United States identified adaptive learning technologies, educational applications of AI, and instructional design as innovative technologies and practices for the future of higher education. Adaptive learning technology is defined as a technology that adjusts course content based on an individual's ability or skill level, thus enhancing learners' motivation and improving learning effectiveness (EDUCAUSE, 2020). All three subsequent versions of the report emphasized the importance of AI, adaptive personality learning, and blended learning. Socio-scientific issues are inherently interdisciplinary and cross-cultural (Zeidler, Herman, Ruzek, Linder, & Lin, 2013), making it challenging for many individuals to efficiently gather and analyze a large amount of information within a limited timeframe. Therefore, the model for educating on socio-scientific issues in this study must be constructed based on an AI adaptive environment.

This study pursued the following research objectives:

- A socio-scientific issues education model was developed based on the AI adaptive environment.
- The model was utilized in a physical geology course to assess modifications in the experimenter's critical thinking between pre- and post-course outcomes.

2. Literature Review

Socio-scientific issues (SSIs) are complex and controversial problems that lack structure and involve both scientific and social dimensions (Sadler & Zeidler, 2005； Yun,Shi & Jun, 2020). The controversial nature of SSIs arises from the varied judgments and perceptions held by individuals and groups, that are shaped by cultural, social, and political factors (Osborne & Dillon, 2008). The study of SSIs originates from the Science, Technology, and Society (STS) education movement of the 1970s. Common points between SSIs and STS are that both are based on sustainable development, and social issues induced by science and technology are controversial; therefore, rational reflection and decision-making based on cross-culture are needed. Further, both tend towards issue-oriented education. While some scholars have integrated social science issues into science education, others have used social science issues to lead to corresponding scientific knowledge (Wang, 2014). Differences include the fact that STS focuses on connecting society to science and technology while SSIs emphasize the development of content knowledge, character, and virtues (Zeidler, Sadler, Simmons, & Howes, 2005). It can be argued that the instruction of SSIs is a reconstruction and development of STS, which not only provides a means to address the social implications of science and technology, but also a way to tap into people's personal philosophies and belief systems (Zeidler et al., 2005). Li 2022 summarized the six elements of the SSIs instructional model in a networking session at AISL in China:

- Entry points: Appropriate entry points for SSIs are identified based on science content to place issues into context.
- Model derivation: Students are required to complete scientific model development, use, evaluation, and revision activities.
- Systematize: SSIs are complex and involve multidimensional domain knowledge; therefore, students need to integrate fragmented knowledge from different disciplines and derive it systematically.
- Digital literacy: The complex and constantly evolving nature of the knowledge required for SSIs necessitates that students possess digital literacy skills in retrieving, identifying, and analyzing information.
- Thinking from multiple perspectives: SSIs involve the interests of different groups; therefore, students need to think from different standpoints to form a multi-faceted perception.
- Informed opinion or solution: Students need to articulate their opinion or solution and support it with appropriate evidence.

Specific teaching strategies for SSIs include role-playing, debates, practice and examination, writing, and mind mapping (Zhang, 2022). Extensive empirical research has been conducted on how SSI education can improve critical thinking abilities. Glaser (1941) was the first to propose the term critical thinking, which he defined as follows: critical thinking is an attitude that is related to personal experience and tends to consider issues in a reflective manner; it is a skill that enables the use of logical thinking and reasoning. Facione et al. (1995) defined critical thinking as a purposeful and self-regulated process of judgment that involves analysis, evaluation, inference, and interpretation, highlighting that critical thinking includes both dispositions and skills. These studies established the foundation for the creation of critical thinking scales, of which the California Critical Thinking Scale is held in particularly high esteem. The student-centered constructivist approach is widely regarded as superior pedagogy for enhancing critical thinking (Bonk & Smith, 1998). Ennis (1989) described four pedagogical approaches related to improving critical thinking: generalized pedagogy (specialized courses), indoctrination pedagogy (issues), immersion pedagogy (issues and instructional environment), and blended pedagogy (issues and specialized courses). Heyman (2008) suggested to employ collaborative teaching methods to enhance critical thinking. Strategies for instruction comprise debating, practicing, writing, and mind mapping. It is evident that pedagogies aimed to enhance critical thinking share many similarities with the SSI-oriented teaching model:

- All are based on constructivism and are learner centered.
- All teaching strategies involve debate, practice, writing, and mind mapping.
- All emphasize a deep reflective analysis of the problem and sorting out the more reasonable and evidence-supported perspectives.
- Both promote issue-oriented teaching and cooperative learning.

AI brings new paths to SSIs education. Artificial Intelligence in Education (AIED) includes, but is not limited to, intelligent tutoring systems, instructional robots, learning analytics dashboards, adaptive learning systems, and human-computer interaction. It has been recognized as a powerful tool for facilitating curriculum design and development, and for promoting deep learning (Panadero, 2017). Ouyang & Jiao (2021) summarized three paradigms of AIED: (1) Based on the theoretical foundation of behaviorism, AI is the dominant and the learner is the receiver; there is no learner-centeredness. (2) Based on the theoretical foundation of cognitive and social constructivism, AI is the complementary and the learner is the collaborator; it is an exploratory learning environment. The disadvantage is that it lacks the continuous communication or collaboration of human-computer interaction, and learner's initiative needs to be improved. (3) Based on the theoretical basis of connectionism and complex adaptive system, AI is the enabler and the learner is the dominant, which truly realizes both personalized learning and adaptive learning.

In multimodal data collection techniques, AI algorithmic models are key factors to achieve learner-driven, personalized, and adaptive learning (Cukurova, Kent & Luckin, 2019；Khosravi, Sadiq,& Gasevic, 2020). Learner-centered instructional design, self-regulated learning, and critical thinking are important for higher education and social training (Kay, Bartimote, Kitto, Kummerfeld, Liu & Reimann, 2022), as well as for adaptive learning where the learner is the dominant agent. Adaptive learning environments are contexts that are dynamically recorded and adjusted according to the learning situation. This is closely related to AI, personalization, flexibility, interactivity, real-time feedback, the ability to develop a personal learning plan that is better able to increase students' engagement, as well as motivation and potential. Adaptive learning technologies are rapidly developing in massive open online courses (MOOCs) and virtual simulation systems (Capuano & Caballé, 2020). In this study, the physical geology MOOC and Geology Virtual Simulation Platform were used as they can provide a better reference. One of the focal points of research in AIED is the Open Learner Model. Zhou (2022) emphasized that the Open Learner Model necessitates open learning resources, learning environments, learning analytics, learning assessment, learning design, and learning technologies for support. The primary objective of this model is to enhance learner metacognition, drive personalized learning interfaces, emphasize the alignment of learning goals and situations, and serve as drivers for learning data, algorithms, and AI process designs; this model can also provide strong support for self-regulated learning among higher education students (Kay, Bartimote, Kitto, Kummerfeld, Liu & Reimann, 2022). The classic model of self-regulated learning involves planning, monitoring, controlling, evaluating, and reflecting. Self-regulated learning serves as the primary means and embodiment of adaptive learning (Panadero, 2017).

The cross-cultural, interdisciplinary, and controversial nature of SSIs (Zeidler, Herman, Ruzek, Linder, & Lin, 2013) determines the urgency associated with the utilization of AI-enabled adaptive learning systems. AI-enabled adaptive learning environments place higher demands on critical thinking.

3. Model Construction

There is currently no educational model for SSIs that is based on Artificial Intelligence Adaptive Learning Environments (AIALE). This paper explores the literature on SSIs, AIALE, and critical thinking to provide a brief summary of their relationship. SSIs are an effective educational method used to enhance scientific literacy. AIALE serves as a prominent teaching system, and critical thinking plays a crucial role in teaching SSIs and using AIALE. Implementation of SSIs and AIALE can also foster critical thinking. Then, the contents of "learner-centeredness", "constructivism", "multiple perspectives", "systematic derivation", "collaborative inquiry", "digital literacy", and "planning-monitoring-controlling-assessing-reflecting" are systematically analyzed. These items are related to the three components. A foundation is built for constructing the SSIs education model based on the adaptive environment of AI.

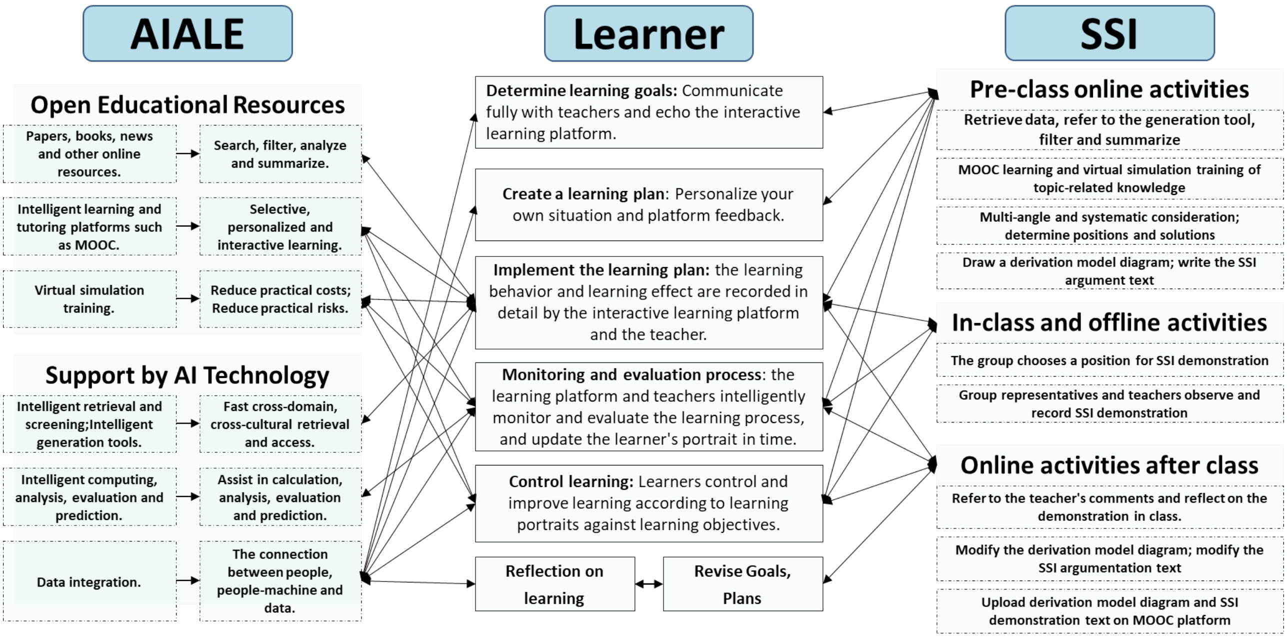

Fig. 1 Socio-scientific issues model based on artificial intelligence adaptive environment

4. Method

4.1. Research Design

This study employed a quasi-experimental design based on the research objectives. The independent variable was whether the SSI teaching method was utilized. The dependent variable was critical thinking, which was measured both before and after the experiment in both experimental and control groups. The following variables were controlled:

- Teaching content: This was the same for both groups, as both have taken a physical geology course.
- Instructional time: This was the same for both groups; both 60 h.
- Statistical control: Both groups were administered pre- and post-tests to measure their critical thinking dispositions and skills.
- Measurement process: The purpose of this study was not explained to both groups to mitigate potential Henry or Hawthorne effects.
- Learners: Both groups were freshmen geology majors: 83% had a prior educational background in the sciences, 73% were from rural areas, 99% were male, and none had received SSI education or improved critical thinking education before the experiment.
- Teachers: Both teachers have 8 years of teaching experience.

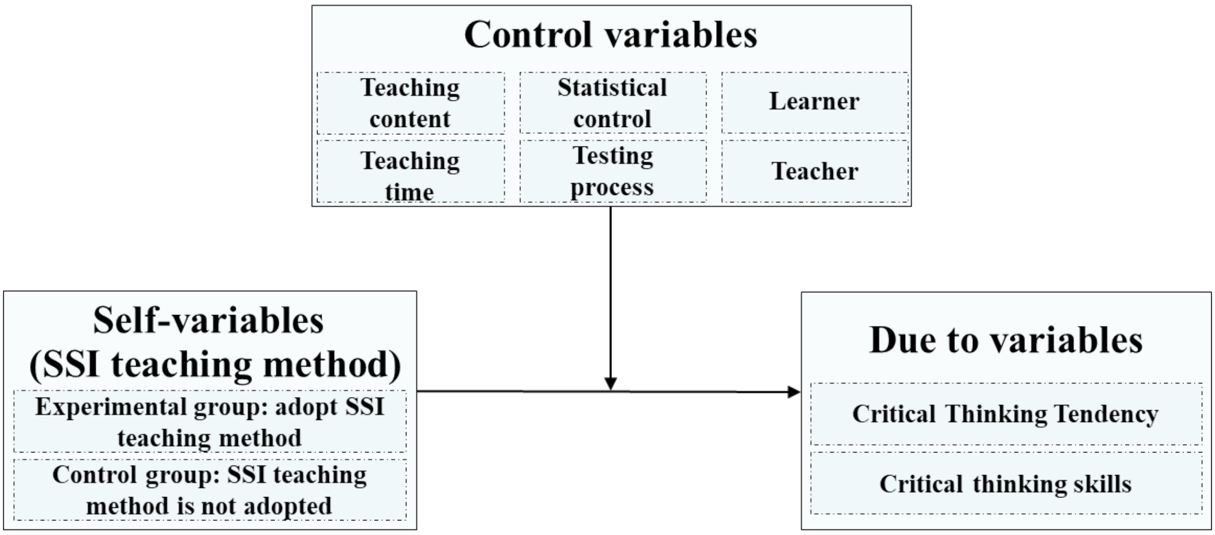

Fig. 2 Research architecture

4.2. Assessment Tool

- Critical thinking dispositions measurement tool: This study utilized the Critical Thinking Dispositions Scale as the measurement tool, which was streamlined by Yu and Yu (2020) and based on the California Critical Thinking Dispositions Inventory.
- Critical Thinking Skills Measurement Tool: This paper employed the Chinese version of the California Critical Thinking Skills Test, revised by Luo in 2002.

4.3. Instructional Design

Instead of treating SSIs as a distinct course, this study chose relevant SSIs to incorporate into each module of the physical geology course based on the content of the module. SSI-oriented teaching is conducted through several activities, including the analysis of SSI-related data, the creation of derivation diagrams, the writing of argumentative texts, and engagement in debate. Based on the scientific and technological hotspots in the field of geology and its cross-cutting areas, and in conjunction with current social news, related SSIs were incorporated into the teaching. The SSIs selected for this study were not limited to hot topics such as nuclear energy, energy, and genetics, but were chosen based on course content.

Table 1. Socio-scientific issue (SSI)-oriented instructional design for the teaching of "mineral identification" as an example

Teaching content	Pre-course activities	In-class activities	Post-course activities
Mineral identification	(1) Watch the "Mineral Identification" instructional video in the MOOC and complete the pre-test. (2) Search for information related to this SSI, including background information on the topic, cross-cutting knowledge (new energy vehicles, oil, coal, and power generation); then, systematically analyze and summarize.	Teaching places: mineral and rock identification training room, outdoor geological surveyor examination point. (1) Contextual Introduction - Knowledge Inquiry - Practical inquiry. (2) SSI arguments related to minerals: New energy vehicle batteries are inseparable from lithium, nickel, and cobalt ore, all of which are non-renewable minerals; then, new energy vehicles are vigorously promoted, so that fuel vehicles gradually withdraw from the market. Is this approach still meaningful? How to decide? Please choose a position among a new energy	(1) Complete post-course assignments at the massive open online course. (2) Upload revised SSI derivation model diagrams and SSI argumentation text at

	(3) Hands-on training in a geological virtual simulation platform. (4) Production of a diagram of the derivation model for SSI. (5) Writing SSI argumentative text.	vehicle enterprise, the resource sector, and the environmental sector to argue. Put forward perspectives, list the evidence, and summarize the conclusions, from professional knowledge, ethical morality, social development, and comprehensive consideration perspectives. (3) Observation and evaluation.	massive open online course.

5. Analysis of Results

5.1. Critical Thinking Dispositions

According to Tables 2 and 3, the means of the pre-test scores of the two groups were 139.65 and 138.57, respectively. The Levene's test for homogeneity of variance indicated non-significance ($F = 2.322$, $p = 0.131 > 0.05$), indicating that there was no significant difference between the two groups in terms of pre-test dispersion scenarios. The results of the t-test assuming equal variance indicated that there was no significant difference in the pre-test scores among the two groups. Therefore, the two groups were compared on a more consistent premise and are suitable for analysis of covariance.

Table 2. Summary table of descriptive statistics for measures of critical thinking dispositions in experimental and control groups

Groups	Time	Count	Min.	Max.	Mean	Standard Deviation	Variance	Standard Error of Mean
Experimental Group	pre-test	52	120	159	139.6538	9.53607	90.9366	1.32242
	post-test	52	129	165	148.5577	8.40031	70.5652	1.16491
Control Group	pre-test	49	116	152	138.5714	8.28402	68.6250	1.18343
	post-test	49	118	152	139.2449	7.85157	61.6472	1.12165

Table 3. Experimental and control groups critical thinking dispositions pre-test independent sample t-tests

Pre-test Scores	Levene's Test		T-test						
	F-test	Significance	t	Degree of freedom	2-Tailed significance	Mean Deviation	Standard Error of the Difference	95% Confidence Interval	
								Lower limit	Upper Limit

Assumption of Equal Variances	2.322	0.131	0.607	99	0.545	1.082	1.7821	-2.454	4.618

To conduct an independent samples one-way covariate analysis, the assumption of homogeneity of regression coefficients within the group should be tested. Whether the slopes obtained from regression analysis of the covariates on the dependent variable are equal in each group should also be tested before conducting the covariate analysis. As shown in Table 4, the interaction between the dependent variable and the covariates of the Critical Thinking Dispositions Test did not reach the level of significance ($F = 3.364$, $p = 0.07 > 0.05$), indicating no interaction. The regression line slopes for both groups are identical, where pretest scores are the main effect and pretest scores*groups are the interaction. The results of the analysis suggest that the relationship between pretest scores (covariates) and posttest scores (dependent variable) remains constant across different levels of the treatment for independent variables. In other words, the regression analyses showed no difference in slopes, indicating that the analysis of covariates can proceed.

Table 4. Summary table for analyzing homogeneity of regression coefficients among groups in the Critical Thinking Dispositions Test

Source	Stdev square	Degree of freedom	Mean square	F	p
Adjusted Pattern	8394.058[a]	3	2798.019	771.519	0.000
Intercept	159.667	1	159.667	44.026	0.000
Groups	37.437	1	37.437	10.323	0.002
Pre-test	6108.273	1	6108.273	1684.280	0.000
Interaction (Group*Pre-test)	12.200	1	12.200	3.364	0.070
Residual	351.784	97	3.627		
Total	2104234.000	101			
Adjusted Total	8745.842	100			

a.R Squared=0.960(Adjusted R Squared=0.959)

Table 5 shows that the full model to predict the dependent variable reaches significance: r square 0.958, $p = 0 < 0.01$; this result indicates that this model has explanatory power. After removing the impact of pretest scores on post-test scores for the critical thinking dispositions measure, the effect of the covariate produced a significant $F(1,98) = 1667.666$, $p < 0.01$, indicating strong explanatory power of the covariate for the dependent variable. Therefore, post-test scores vary significantly based on the experimental treatments administered to the subjects. This study found a significant between-group effect, $F(1,98) = 472.534$, $p = 0 < 0.01$, indicating that the critical thinking dispositions of college students can be significantly influenced by SSI instructions based on AI adaptive environment, which can be compared post-hoc.

Table 5. Summary table for independent samples one-way analyses of the measure of critical thinking dispositions

Source	Stdev square	Degree of freedom	Mean square	F	p
Adjusted Pattern	8381.858[a]	2	4190.929	1128.378	0.000
Intercept	179.497	1	179.497	48.328	0.000
Covariate (Pre-test)	6193.905	1	6193.905	1667.666	0.000
Groups	1755.046	1	1755.046	472.534	0.000
Residual	363.983	98	3.714		
Total	2104234.000	101			
Adjusted Total	8745.842	100			

a.R Squared=0.958(Adjusted R Squared=0.958)

As shown in Table 6, the adjusted post-test mean was 148.08 for the experimental group and 139.72 for the control group. The results show that the experimental group performed significantly better than the control group. This result indicates that the AI adaptive environment-based SSIs instruction resulted in a significant difference in the performance of the experimental and control group students on the Critical Thinking Dispositions Test. This further indicates that the AI adaptive environment-based SSIs instruction was effective in enhancing the critical thinking dispositions of the experimental group.

Table 6. Statistical table of adjusted post-test mean for the Critical Thinking Dispositions Test

Groups	Count	Adjusted Post-test Mean	Standard Error
Experimental Group	52	148.08	0.022
Control Group	49	139.72	0.022

Experimental Group=148.5577-0.884*(139.6538-139.1126)
Control Group =139.2449-0.884*(138.5714-139.1126)

5.2. Critical Thinking Skills

According to Tables 7 and 8, the mean of the pre-test scores of the two groups were 20.81 and 20.45, respectively. The Levene's test for homogeneity of variance resulted was non-significant ($F = 0.019$, $p = 0.6 > 0.05$), indicating that there was no significant difference between the two groups in terms of pre-test dispersion scenarios. The results of the t-test assuming equal variance indicated that there was no significant difference in the pre-test scores between the two groups. Therefore, the two groups were compared on a more consistent premise and are suitable for analysis of covariance.

Table 7. Summary table of descriptive statistics for measures of critical thinking skills in experimental and control groups

Groups	Time	Count	Min.	Max.	Mean	Standard Deviation	Variance	Standard Error of Mean
	pre-test	52	13	28	20.81	3.413	11.649	0.473

Experimental Group	post-test	52	13	31	23.65	4.297	18.466	0.596
Control Group	pre-test	49	13	28	20.45	3.434	11.794	0.491
	post-test	49	10	30	21.39	4.076	16.617	0.582

Table 8. Experimental and control groups critical thinking skills pre-test independent sample t-tests

Pre-test Scores	Levene's Test		T-test						
	F-test	Significance	t	Degree of freedom	2-Tailed significance	Mean Deviation	Standard Error of the Difference	95% Confidence Interval	
								Lower limit	Upper Limit
Assumption of Equal Variances	0.019	0.892	0.526	99	0.6	0.359	0.682	-1.711	0.994

To conduct independent samples one-way covariate analysis, the assumption of homogeneity of regression coefficients within the group should be tested. Whether the slopes obtained from regression analysis of the covariates on the dependent variable are equal in each group should also be tested before conducting the covariate analysis. As shown in Table 9, the interaction between the dependent variable and the covariates of the Critical Thinking Skills Test did not reach the level of significance ($F = 0.580$, $p = 0.448 > 0.05$), indicating no interaction. The regression line slopes for both groups are identical, with pretest scores being the main effect and pretest scores*groups as the interaction. The analysis suggests that the relationship between pretest scores (covariates) and posttest scores (dependent variable) remains constant across different levels of the treatment for independent variables. In other words, the regression analyses identified no difference in slopes, indicating that the analysis of covariates can proceed.

Table 9. Summary table for analyzing homogeneity of regression coefficients among groups in the Critical Thinking Skills Test

Source	Stdev square	Degree of freedom	Mean square	F	p
Adjusted Pattern	1423.538[a]	3	474.513	103.337	0.000
Intercept	1.587	1	1.587	0.346	0.558
Groups	0.005	1	0.005	0.001	0.973
Pre-test	1287.752	1	1287.752	280.441	0.000
Interaction (Group*Pre-test)	2.664	1	2.664	0.580	0.448
Residual	445.412	97	4.592		
Total	53248.000	101			
Adjusted Total	1868.950	100			

a.R Squared=0.762(Adjusted R Squared=0.754)

Table 10 shows that the full model to predict the dependent variable reaches significance at an R square of 0.760 ($p < 0.01$). Judging from the significance, this model has explanatory power. After removing the impact of pretest scores on post-test scores for the critical thinking skills measure, the effect of the covariate produced a significant $F(1,98) = 282.429$, $p = 0 < 0.01$, indicating a strong explanatory power of the covariate for the dependent variable. Post-test scores vary significantly based on the experimental treatments administered to the subjects. The study found a significant between-group effect, $F(1,98) = 472.534$, $p = 0 < 0.01$, indicating that college students' critical thinking skills can be significantly influenced by SSI instruction based on the AI adaptive environment, which can be compared post-hoc.

Table 10. Summary table for independent samples one-way analyses of the measure of critical thinking skills

Source	Stdev square	Degree of freedom	Mean square	F	p
Adjusted Pattern	1420.874[a]	2	710.437	155.382	0.000
Intercept	1.525	1	1.525	0.334	0.565
Covariate (Pre-test)	1291.326	1	1291.326	282.429	0.000
Groups	89.641	1	89.641	19.606	0.000
Residual	448.076	98	4.572		
Total	53248.000	101			
Adjusted Total	1868.950	100			

a.R Squared=0.760(Adjusted R Squared=0.755)

In reference to Table 11, the data show that the adjusted post-test mean for the experimental group was 22.36 and that for the control group was 21.58; the experimental group performed significantly better than the control group. This result indicates that the AI adaptive environment-based SSI instruction resulted in a significant difference in the performance of the experimental and control group students on the Critical Thinking Skills Test. The AI adaptive environment-based SSIs instruction was effective in enhancing the critical thinking skills of the experimental group.

Table 11. Statistical table of adjusted post-test mean for the Critical Thinking Skills Test

Groups	Count	Adjusted Post-test Mean	Standard Error
Experimental Group	52	22.36	0.063
Control Group	49	21.58	0.063

Experimental Group=22.55-1.055*（20.81-20.63）
Control Group =21.39-1.055*（20.45-20.63）

5.3. Critical Thinking Dispositions and Critical Thinking Skills

The central tendency of critical thinking dispositions and skills to the control scores (60%, 70%, and 80% of the total score) was compared between both groups. The central tendency on the pre and post tests for critical thinking dispositions exceeded 80% of the total score, whereas the concentration on the pre and post tests for critical thinking skills remained below 70% of the total score. Both the experimental group and the control group exhibited a distinct "high disposition and low skill" pattern in critical thinking, as evidenced by the results presented in Tables 12 and 13.

Table 12. Comparison of central tendency and control scores for critical thinking dispositions

Groups	Time	Control Scores（168 *0.8）	Mean	Median	Mode
Experimental Group	pre-test	134.4	139.6538	138	135
	post-test		148.5577	148	142
Control Group	pre-test		138.5714	140	135
	post-test		139.2449	140	135

Table 13. Comparison of central tendency and control scores for critical thinking skills

Groups	Time	Control Scores（34*0.6）	Mean	Median	Mode	Control Scores（34*0.7）
Experimental Group	pre-test	20.4	20.81	21	19	23.8
	post-test		23.65	24	23	
Control Group	pre-test		20.45	20	18	
	post-test		21.39	22	19	

6. Conclusion

This study provides initial evidence that incorporating personalized socio-scientific issues through AI adaptive platforms into college courses can significantly improve critical thinking dispositions and skills, two core competencies needed for 21st century citizenship and careers. The "high disposition, low skill" pattern also suggests a need to better integrate critical thinking skill-building with the SSI curriculum. Further research should examine the effects of the model with larger, more diverse student samples, expanded outcome measures, and longer interventions. Refining this model to enhance critical analysis of real-world problems has important implications for learning theory, instructional design, teacher education, and education technology.

References

Capuano, N., & Caballé, S. (2020). *Adaptive Learning Technologies. AI Magazine, 41(2)*, 96-98. https://doi.org/10.1609/aimag.v41i2.5317

Chassignol, M., Khoroshavin, A., Klimova, A., & Bilyatdinova, A. (2018). *Artificial Intelligence trends in education: a narrative overview. Procedia Computer Science, 136*, 16–24. https://doi.org/10.1016/J.PROCS.2018.08.233

Chen, L., Chen, P., & Lin, Z. (2020). *Artificial Intelligence in Education: A Review. IEEE Access, 8*, 75264–75278. https://doi.org/10.1109/access.2020.2988510

Chin,C.C., &Wu,C.Y.(2017). *Elementary Students' Perception of Socioscientific Issue-basedLearning Environment — Perspectives of Personal Learning Motivation,Group Cooperative Ability, and the Classroom Environment. Journal of Education*, 45(1), 71-97.

Chung, Y., Yoo, J., Kim, SW. et al.(2016) *Enhancing students' communication skills in the science classroom through socio-scientific issues. International Journal of Science and Mathematics Education, 14*, 1–27. https://doi.org/10.1007/s10763-014-9557-6

Cukurova, M., Kent, C., & Luckin, R. (2019). *Artificial intelligence and multimodal data in the service of human decision-making: A case study in debate tutoring. British Journal of Educational Technology.* https://doi.org/10.1111/bjet.12829

Eastwood, J., Sadler, T., Zeidler, D., Lewis, A., Amiri, L., & Applebaum, S. (2012). *Contextualizing nature of science instruction in socio-scientific issues. International journal of Science Education, 34(15),* 2289-2315. http://dx.doi.org/10.1080/09500693.2012.667582

EDUCAUSE. (2020). *The Horizon Report: 2020 Higher Education Edition*. EDUCAUSE.

Ennis, R. H. (1989). *Critical Thinking and Subject Specificity: Clarification and Needed Research. Educational Researcher, 18(3)*, 4–10. http://dx.doi.org/10.3102/0013189x018003004

Facione, P. A., Sanchez, C. A., Facione, N. C., & Gainen, J. (1995). *The disposition toward critical thinking. The Journal of general education, 44(1)*, 1-25. http://dx.doi.org/10.2307/27797240

Glaser, E. M. (1941). *An Experiment int he Development of Critical Thinking. Teachers College Contributions to Education,(843)*.

Guo, Z. . (2016). *The cultivation of 4c's in china—critical thinking, communication, collaboration and creativity. DEStech Transactions on Social Science Education and Human Science(emass)*.

He,P.W.(2016). *Promoting college student critical thinking disposition and competency through socio-scientific issue discussions.* Master's thesis. National Sun Yat-sen University

Heyman, G. D. (2008). *Children's Critical Thinking When Learning From Others. Current Directions in Psychological Science, 17(5)*, 344–347. https://doi.org/10.1111/j.1467-8721.2008.00603.x

Huang,S.M.(1999). *Cultivating Student Knowledge and Creativity through STS Module Teaching: (i) Food Additives and (ii) Colorings.* Master's thesis. National Taiwan Normal University

Kay, J., Bartimote, K., Kitto, K., Kummerfeld, B., Liu, D., & Reimann, P. (2022). *Enhancing learning by Open Learner Model (OLM) driven data design. Computers and Education: Artificial Intelligence, 3.* https://doi.org/10.1016/j.caeai.2022.100069

Khosravi, H., Sadiq, S., & Gasevic, D. (2020). *Development and Adoption of an Adaptive Learning System. Proceedings of the 51st ACM Technical Symposium on Computer Science Education.* https://doi.org/10.1145/3328778.3366900

Murcia, K. (2007). *Science for the 21st century : teaching for scientific literacy in the primary classroom. Teaching Science; v.53 n.2 p.16-19; Winter 2007, 53(2),* 16–19. https://search.informit.org/doi/10.3316/aeipt.160342

Ouyang, F., & Jiao, P. (2021). *Artificial intelligence in education: The three paradigms. Computers and Education: Artificial Intelligence, 2, 100020*. https://doi.org/10.1016/j.caeai.2021.100020

Panadero, E. (2017). *A Review of Self-regulated Learning: Six Models and Four Directions for Research. Frontiers in Psychology, 8*. https://doi.org/10.3389/fpsyg.2017.00422

Yager, R. E. (1995). *Science/Technology/Society: A Reform Arising from Learning Theory and Constructivist Research.* Paper presented at the Annual Meeting of the American Educational Research Association, San Francisco, CA, April 18-22, 1995.

Yun, A., Shi, C., & Jun, B. G. (2020). *Dealing with Socio-Scientific Issues in Science Exhibition: a Literature Review. Research in Science Education.* https://doi.org/10.1007/s11165-020-09930-0

Zeidler, D. L., Sadler, T. D., Simmons, M. L., & Howes, E. V. (2005). *Beyond STS: A research-based framework for socio-scientific issues education. Science Education, 89(3)*, 357–377. http://dx.doi.org /10.1002/sce.20048

Zeidler, D. L., Herman, B. C., Ruzek, M., Linder, A., & Lin, S. S. (2013). *Cross-cultural epistemological orientations to socio-scientific issues. Journal of Research in Science Teaching, 50(3)*, 251-283. https://doi.org/10.1002/tea.21077

Zhang,M.Y.(2022). *Research on Chemistry Teaching of cultivating students' social responsibility based on Socio-scientific Issues.* Master's thesis. Shandong Normal University

Zhou, Z. H. (2022). *Open-environment machine learning. National Science Review, 9(8),* nwac123. https://doi.org/10.1093/nsr/nwac123