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Active learning and design thinking effects on pre-service science teachers' analytical thinking and achievement motivation

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Abstract

This quasi-experimental study (N = 80) investigated the combined effects of active learning (AL) and design thinking (DT) on pre-service science teachers' analytical thinking (AT) and achievement motivation (AM) at a Thai university. Grounded in self-determination theory, it proposes, as a theoretical interpretation, a "dual-pathway account" in which DT may support autonomy and AL may support competence. The 12-week intervention produced a significant multivariate effect (η^2_p = .18). The experimental group outperformed the control group on AT (d = 0.69) and AM (d = 0.58), with a large within-group motivation gain (d_z = 0.91). These effects were larger than benchmarks for either approach alone, but such cross-study comparisons are interpretive rather than confirmatory. The findings provide preliminary evidence that the combined model is more effective than conventional instruction and warrant confirmation through factorial designs.

Keywords: analytical thinking, achievement motivation, active learning, design thinking, self-determination theory, pre-service science teachers

INTRODUCTION

The global transition toward the digital era and the knowledge society has imposed unprecedented challenges on educational systems worldwide. As society evolves from Industry 4.0 to Society 5.0, the focus shifts from mere efficiency to human-centric value creation (González-Pérez et al., 2023). The future of jobs report 2023 (World Economic Forum, 2023) identifies analytical thinking (AT) and creative thinking as the paramount skills demanded by the labor market. Shahidi Hamedani et al. (2024) assert that in the Education 5.0 landscape, workforce readiness depends not just on technical skills but on high-order cognitive abilities to navigate complex, technology-embedded environments. Aripin et al. (2021) emphasize that AT is the cornerstone for students to filter and process the massive influx of information in the 5.0 era.

Carayannis and Morawska-Jancelewicz (2022) propose that Education 5.0 prioritizes the full development of individuals by merging knowledge, skills, and wisdom to generate societal impact. However, science education in Southeast Asia faces critical hurdles. The PISA 2022 results reveal that students in the region achieved scores significantly below the OECD (2023) average, with systemic deficiencies rooted in teacher preparation programs that adhere to outdated transmission models (Strat et al., 2024; Tondeur et al., 2019). This challenge is particularly acute in contexts where governments have embarked on ambitious trajectories of national transformation, mandating shifts from labor-intensive economies to value-based, innovation-driven economies (National Strategy Secretariat Office, 2018; Sangwanglao, 2024). Yet, empirical evidence on effective instructional models for achieving these goals in pre-service teacher education remains notably scarce, especially in regional universities where resource limitations compound the transition from traditional pedagogy to innovation-based instruction (Fry & Bi, 2013). Consequently, a fundamental research question arises: Which instructional model can effectively enhance both AT and achievement motivation (AM) among pre-service science teachers?

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Contribution to the literature

- This study develops and provides preliminary quasi-experimental evidence for a combined AL-DT instructional model designed for pre-service science teacher education within the Education 5.0 framework.
- It proposes a theoretical "dual-pathway" account, grounded in SDT, in which DT may primarily support autonomy needs while AL may support competence needs. Because these psychological needs were not directly measured, the account is offered as an interpretation to be tested in future research.
- It addresses a critical contextual gap by providing quasi-experimental evidence from a Thai university setting, where empirical research on innovative pedagogies for teacher education remains notably scarce.

Design thinking (DT) has emerged as a pivotal pedagogical strategy within the Education 5.0 framework. Defined as a human-centered process comprising empathize, define, ideate, prototype, and test (Razzouk & Shute, 2012), DT significantly enhances analytical capabilities (Henriksen et al., 2017), team psychological safety, and creative confidence (Panke, 2019). Meta-analytic evidence indicates that DT has an upper-medium positive effect on student learning, engagement, and problem-solving (Yu et al., 2024), and enhances creativity in STEM contexts (Muneer et al., 2025), while integrated STEM curricula can cultivate design-thinking dispositions (Thomason & Hsu, 2025). Gagaza (2025) proposed that integrating DT with generative AI empowers teachers to create more personalized learning experiences. However, scholars note potential limitations in maintaining sustained cognitive engagement throughout the rigorous iterative process (Wrigley & Straker, 2017), prompting the need for a complementary pedagogical approach.

Active learning (AL) serves as the pedagogical cornerstone of the Education 5.0 paradigm. Characterized by active engagement through discussion and collaborative problem-solving (Bonwell & Eison, 1991), AL possesses a robust empirical foundation. Freeman et al.'s (2014) seminal meta-analysis established that AL increases academic performance (ES = 0.47). Related active-learning approaches show comparable benefits: project-based learning yields medium-to-large gains in achievement (Chen & Yang, 2019; Zhang & Ma, 2023), and problem-based and inquiry-based learning improve critical thinking, including in science (Arifin et al., 2025; Liu & Pásztor, 2022). Double et al. (2020) validated that peer assessment substantially improves achievement via social information processing, while Lehtinen et al. (2023) found that socioemotional interaction in collaborative learning supports engagement and reduces isolation among pre-service teachers.

Self-determination theory (SDT) serves as the theoretical lens to elucidate the mechanism underlying this integration (Ryan & Deci, 2020). SDT asserts that intrinsic motivation arises from the fulfillment of autonomy, competence, and relatedness (Guay, 2022). Howard et al. (2021) confirmed that satisfying these needs is the strongest predictor of deep learning, and the satisfaction of these needs predicts autonomous motivation (Bureau et al., 2022).

Research Gaps and Hypotheses

A review of the literature identified four distinct research gaps:

(a) theoretical fragmentation regarding the potential combined use of AL and DT within Education 5.0;

(b) contextual scarcity of studies in teacher education within Thailand and the wider Southeast Asian region;

(c) methodological opacity in reporting effect sizes and confidence intervals (CIs); and

(d) mechanistic ambiguity regarding the psychological pathways through which AL-DT models influence AT (Minet et al., 2024).

This study synthesizes a conceptual framework integrating social constructivism (Vygotsky, 1978), SDT (Ryan & Deci, 2020), and the Education 5.0 paradigm (Carayannis & Morawska-Jancelewicz, 2022). The framework proposes that DT promotes autonomy (McLaughlin et al., 2019), AL improves competence (Theobald et al., 2020), and collaborative interaction fulfills relatedness (Lehtinen et al., 2023). Three hypotheses were tested:

Because the present design compares the combined AL-DT model with conventional instruction only, the hypotheses below concern the overall effectiveness of the combined model relative to conventional instruction; they do not isolate the unique contributions of AL or DT, nor do they test the dual-pathway mechanism directly.

H1: Students instructed via the AL-DT model will exhibit significantly higher combined mean vectors of AT and AM compared to the conventional instruction group ($p < .05$).

H2: The AL-DT model will produce a statistically significant and practically meaningful multivariate effect on the combined outcomes relative to conventional instruction.

H3: Students in the experimental group will demonstrate a significant increase in post-test AM relative to pre-test.

MATERIALS AND METHODS

Research Design

This study employed a quasi-experimental research design, specifically the nonequivalent control group pre-test-post-test design (Shadish et al., 2002). Because participants were not randomly assigned as individuals, reporting follows the TREND statement for nonrandomized evaluations (Des Jarlais et al., 2004) rather than the CONSORT statement (Schulz et al., 2010).

Participants

The population consisted of 180 second-year undergraduate students majoring in science education at a university in Thailand, enrolled in a "learning management science" course during the first semester of the 2025 academic year. Sample size was determined using a priori power analysis via G*Power 3.1.9.7 (Faul et al., 2007), based on a medium effect size (f^2 = 0.15), α = .05, and power (1 - β) = .80, yielding a minimum of 68 students. The final sample consisted of 80 students in two intact classrooms. Because only two intact classes were available, one class was assigned to the experimental condition (n = 40, AL-DT model) and the other to the control condition (n = 40, conventional instruction); individual students were not randomly assigned, so each condition comprised a single intact class.

Instruments

AL-DT instructional plans

The experimental intervention comprised 12 lesson plans (4 hours/week, 48 hours total). The pedagogical framework integrated the DT process (IDEO, 2012) with AL principles (Bonwell & Eison, 1991). Content validity was verified by five experts (item-objective congruence [IOC] range: 0.75-0.93). Instructional effectiveness met the 80/80 mastery learning standard (Guskey, 2023) with a ratio of 82.47/81.43.

Each 4-hour weekly session followed the AL-DT sequence. The lesson opened with an empathize/define phase in which students conducted brief empathy fieldwork with school learners to frame an authentic science-teaching problem; an Ideate phase used active-learning routines (think-pair-share, small-group brainstorming, and peer feedback) to generate instructional solutions; and a prototype/test phase in which groups built and trialed a micro-lesson or learning material and revised it after feedback. Throughout, the instructor acted as a facilitator—posing questions, managing group work, and providing formative feedback—rather than delivering content, while students worked in collaborative teams and documented their reasoning in a design journal. Assessment combined the design artifact, the journal, and a group presentation. The control group covered the same content and learning objectives through conventional lecture and teacher-led demonstration over the same 48 hours.

Analytical thinking ability test

A 50-item multiple-choice test based on the new taxonomy of educational objectives (Marzano & Kendall, 2006) targeted the analysis and knowledge-utilization levels (maximum score = 50). A sample item asked students to compare two experimental procedures and identify the variable responsible for a discrepant result. Difficulty indices ranged from 0.40 to 0.78, discrimination indices from 0.35 to 0.70, and KR-20 reliability was 0.86.

Achievement motivation scale

A 20-item, 5-point Likert scale (1 = strongly disagree to 5 = strongly agree; possible range 20 to 100) grounded in AM theory and achievement goal theory (Anderman, 2020; Schunk et al., 2014; Struck Jannini et al., 2024) and SDT (Ryan & Deci, 2020), comprising items on task persistence, mastery orientation, and effort (e.g., "I keep working on a difficult task until I understand it"). CFA indicated good model fit (χ^2/df = 1.87, CFI = .96, TLI = .95, RMSEA = .047, SRMR = .038). Cronbach's α = .89. The scale was translated into Thai and back-translated and was piloted with a comparable group prior to use.

Procedures

The study was conducted over 14 weeks in three phases: phase 1 (week 1) involved pre-test administration; phase 2 (week 2-week 13) comprised the intervention, during which the experimental group engaged in the AL-DT model (including empathy fieldwork, collaborative brainstorming, and rapid prototyping) while the control group received conventional instruction; phase 3 (week 14) involved post-test administration. The same instructor taught both groups.

Implementation fidelity

To ensure the AL-DT intervention was delivered as intended and to minimize instructor effects, implementation fidelity was systematically monitored and quantified.

Observation procedures and criteria: Two independent educational experts, blinded to the specific research hypotheses, conducted direct classroom observations for 25% of the total instructional time (three of the 12 intervention weeks, randomly selected). Fidelity was assessed using a structured 15-item observational rubric developed for this study, evaluating three core domains:

(a) adherence to the DT iterative phases,

Table 1. Quality assessment of innovation, sample equivalence, and MANCOVA assumptions

Assessment domain	Indicator	Statistics/value	Criterion	Interpretation
1. Innovation quality	Content validity (IOC)	M = 0.84	≥ 0.50	Acceptable
	Instructional effectiveness	82.47/81.43	≥ 80/80	Met mastery standard
	Effectiveness index	E.I. = 0.68	≥ 0.50	High gain
2. Sample equivalence	Gender distribution	$\chi^2(1, N = 80) = 0.45$	$p > .05$	Equivalent ($p = .502$)
	Age	$t\,(78) = 0.32$	$p > .05$	Equivalent ($p = .750$)
	GPA	$t\,(78) = -0.58$	$p > .05$	Equivalent ($p = .564$)
	Pre-test (AT)	$t\,(78) = 0.41$	$p > .05$	Equivalent ($p = .683$)
	Pre-test (AM)	$t\,(78) = 0.27$	$p > .05$	Equivalent ($p = .788$)
3. MANCOVA assumptions	Normality (AT)	$W = .971$	$p > .05$	Met ($p = .089$)
	Normality (AM)	$W = .968$	$p > .05$	Met ($p = .072$)
	Homogeneity of variance (AT)	$F\,(1, 78) = 1.24$	$p > .05$	Met ($p = .269$)
	Homogeneity of variance (AM)	$F\,(1, 78) = 0.89$	$p > .05$	Met ($p = .348$)
	Homogeneity of covariance	Box's M = 4.52	$p > .05$	Met ($p = .221$)
	Homogeneity of regression slopes	$F\,(2, 73) = 0.68$	$p > .05$	Met ($p = .510$)

(b) facilitation of active student-engagement strategies, and

(c) avoidance of traditional passive lecturing.

Observer training and agreement: Prior to the observations, the two raters completed a calibration session in which they scored a 60-minute recorded pilot lesson and discussed discrepancies until consensus was reached. For the intervention sessions, inter-rater reliability was calculated using Cohen's kappa (κ), which yielded κ = 0.84, indicating strong agreement between the independent observers (McHugh, 2012).

Quantitative indicators of fidelity: Analysis of the observational rubrics revealed an average implementation compliance rate of 88.5% across all observed sessions. These indicators confirm that the AL-DT model was executed with high structural and pedagogical fidelity, supporting the internal validity of the study's findings.

Data Analysis

Descriptive statistics (mean [M], standard deviation [SD], skewness, and kurtosis) were computed. Assumptions for MANCOVA were verified through Shapiro-Wilk, Levene's, Box's M, and homogeneity of regression slopes tests. Between-group comparisons used one-way MANCOVA controlling for the corresponding pre-test scores as covariates. The pre-test covariates were significant predictors of the post-test outcomes. Within-group comparisons used paired-samples t-tests. Effect sizes included multivariate η^2_p, Cohen's d, Hedges' g, and within-subject Cohen's d_z (Cohen, 1988). Bias-corrected bootstrap 95% CIs (1,000 resamples) were computed for the adjusted mean differences and the effect sizes.

Ethical Considerations

This research was reviewed and approved through an expedited review by the institutional research ethics committee; the institution name and approval number are withheld here for blind review and are provided on the separate title page. All participants provided written informed consent and were assured of their right to withdraw without penalty.

RESULTS

Model Quality and Baseline Equivalence

The AL-DT instructional model met rigorous quality standards (IOC M = 0.84; effectiveness ratio 82.47/81.43; effectiveness index [EI] = 0.68). The experimental and control groups were equivalent across all baseline characteristics: gender ($\chi^2 = 0.45$, $p = .502$), age ($t = 0.32$, $p = .750$), GPA ($t = -0.58$, $p = .564$), pre-test AT ($t = 0.41$, $p = .683$), and pre-test AM ($t = 0.27$, $p = .788$). All MANCOVA assumptions were met: normality ($W = .971$, $p = .089$; $W = .968$, $p = .072$), homogeneity of variance ($F = 1.24$, $p = .269$; $F = 0.89$, $p = .348$), Box's M (4.52, $p = .221$), and homogeneity of regression slopes ($F = 0.68$, $p = .510$).

Table 1 shows the quality assessment of innovation, sample equivalence, and MANCOVA assumptions.

Between-Group Comparison

The MANCOVA revealed a statistically significant main effect of the instructional model on the combined dependent variables (Wilks' Λ = .82, $F\,(2, 75) = 8.25$, $p < .001$, $\eta^2_p = .18$), indicating that 18% of the variance in combined learning outcomes was explained by the model. This η^2_p is a point estimate in the large range; however, its 95% CI [.04, .29] spans small-to-large values, so the magnitude is interpreted with caution. All alternative multivariate test statistics (Pillai's trace, Hotelling's trace, and Roy's largest root) also yielded significant results ($p < .001$).

Univariate analyses confirmed significant differences in both domains: AT ($M_{adj} = 42.15$ vs. 38.40, $F\,(1, 76) = 9.12$, $p = .003$, $\eta^2_p = .11$, $d = 0.69$) and AM ($M_{adj} = 68.50$ vs. 64.10, $F\,(1, 76) = 6.45$, $p = .013$, $\eta^2_p = .08$, $d = 0.58$). **H1** and

Table 2. Multivariate and univariate analysis of covariance results

Analysis	Statistics	*df*	*p*	Effect size	95% CI	Interpretation
Multivariate	Λ = .82	2, 75	< .001	.18	[.04, .29]	Large (CI spans small-large)
AT (univariate)	*F* = 9.12	1, 76	.003	.11	[.01, .23]	Medium-large
AM (univariate)	*F* = 6.45	1, 76	.013	.08	[.00, .19]	Medium effect

Table 3. Comparison of adjusted means, standard errors, and between-group effect sizes

Dependent variable	Group	*n*	Adjusted mean	Standard error	Mean difference	95% CI of difference	Cohen's *d*
AT	Experimental	40	42.15	0.88	3.75**	[1.28, 6.22]	0.69
	Control	40	38.40	0.88			
AM	Experimental	40	68.50	1.22	4.40*	[0.95, 7.85]	0.58
	Control	40	64.10	1.22			

Note. *p < .05 & **p < .01

Table 4. Paired samples t-test results: Pre-post comparison of achievement motivation in experimental group

Time point	*n*	Mean	*SD*	Mean difference	Standard error	*t*	*df*	*p*	Cohen's d_z	95% CI of *dz*
Pre-test	40	62.15	8.20	-6.35	1.10	-5.77***	39	< .001	0.91	[0.55, 1.26]
Post-test	40	68.50	7.50							

Note. d_z: Within-subject Cohen's *d* & ***p < .001

Table 5. Unadjusted pre- and post-test descriptive statistics by group

Variable	Group	*n*	Pre-test: *M* (*SD*)	Post-test: *M* (*SD*)
AT	Experimental (AL-DT)	40	31.50 (5.20)	42.20 (4.80)
	Control	40	31.00 (5.60)	38.30 (5.10)
AM	Experimental (AL-DT)	40	62.15 (8.20)	68.50 (7.50)
	Control	40	61.65 (8.50)	63.85 (7.90)

Note. Maximum possible score: AT = 50 & AM = 100 & adjusted post-test means (**Table 3**) differ slightly because they control for pre-test covariates

H2 were supported. Because the univariate CIs for the effect sizes include values below conventional "large-effect" thresholds, the univariate effects are interpreted as medium-to-large rather than uniformly large.

Table 2 shows the multivariate and univariate analysis of covariance results.

Table 3 shows the comparison of adjusted *M*s, standard errors, and between-group effect sizes.

Within-Group Comparison

The experimental group exhibited significantly higher post-test AM (*M* = 68.50, *SD* = 7.50) compared to pre-test levels (*M* = 62.15, *SD* = 8.20), $t(39) = -5.77$, $p < .001$. The within-subject effect size was large (d_z = 0.91, 95% CI [0.55, 1.26]). **H3** was supported.

Table 4 shows the paired samples t-test results: Pre-post comparison of AM in experimental group.

Unadjusted pre- and post-test descriptive statistics for both groups on both outcomes are presented in **Table 5**.

DICUSSION

The AL-DT instructional model demonstrates high quality and pedagogical efficacy. The content validity index (IOC = 0.84) confirms theoretical soundness, and the instructional effectiveness (82.47/81.43) surpasses the mastery learning standard (Guskey, 2023). The *EI* = 0.68 indicates a medium-to-high learning gain. The model's integrated design combines DT to introduce empathy-driven challenges (intended to support autonomy) with AL mechanisms that provide hands-on experiences and quick feedback loops (intended to support competence). This aligns with the Education 5.0 framework (Chigbu & Makapela, 2025; Gagaza, 2025), which posits that sustainable learning occurs when human-centric design is combined with active pedagogical engagement.

The effect size for AT (*d* = 0.69) is larger than the benchmark established by Freeman et al.'s (2014) meta-analysis (*d* = 0.47). However, effect sizes from different studies, samples, measures, and designs cannot be directly compared, so this difference is noted descriptively rather than as evidence of a synergistic value-added effect. Through the lens of the ICAP framework (Chi & Wylie, 2014), the AL-DT model may elevate students from "active" or "constructive" modes toward "interactive" mode. During the empathize and Define stages, students engage in systems thinking to negotiate meaning and define complex problems, which may foster deep analytical processing aligned with Education 5.0 competencies (Dehbozorgi et al., 2024).

AM results (d = 0.58) are interpreted through SDT. The model was designed to satisfy three basic psychological needs: autonomy (through DT's freedom to define problems; Crompton & Burke, 2023), competence (through AL's mastery experiences; Reeve & Cheon, 2024), and relatedness (through collaborative co-creation; Howard et al., 2021; Pande & Bharathi, 2020). This is offered as a theoretical interpretation; because autonomy, competence, and relatedness were not directly measured, the proposed need-satisfaction pathway was not empirically tested in this study.

The within-subject effect size for motivation growth (d_z = 0.91, 95% CI [0.55, 1.26]) is larger than the meta-analytic baseline of d = 0.49 reported by Lazowski and Hulleman (2016) for psycho-educational interventions, although such cross-study comparisons are interpretive. This pattern is consistent with, but does not establish, the proposed account in which DT supports autonomy through student agency in problem definition (Panke, 2019) while AL supports competence through iterative feedback (Ryan & Deci, 2020). The CI lying entirely above zero indicates a reliable within-group gain.

Several alternative explanations should be considered. Because each condition comprises a single intact class taught by the same instructor, classroom-level factors (peer dynamics, scheduling, and group composition) are confounded with the treatment, and instructor expectancy effects—differences in enthusiasm, feedback, or support toward the innovative condition—cannot be ruled out. Novelty and Hawthorne effects, and the alignment between the intervention activities and the outcome measures, may also have contributed to the observed differences. These factors, together with the absence of AL-only and DT-only comparison conditions, mean the results should be read as promising but preliminary.

CONCLUSIONS

This study developed and evaluated an AL-DT instructional model grounded in the Education 5.0 framework. The model demonstrated high quality (IOC = 0.84; effectiveness 82.47/81.43) and was associated with significantly greater AT (d = 0.69) and AM (d = 0.58) than conventional instruction, with a multivariate effect that was large as a point estimate (η^2_p = .18) and a large within-group motivational gain (d_z = 0.91). The study proposes a theoretical "dual-pathway" account through SDT, in which DT may stimulate autonomy and AL may enhance competence; this account, and any claim of synergy, requires direct testing in future factorial designs. Important limitations temper these conclusions: the design used only two intact classes (one per condition), so treatment and classroom effects cannot be separated; it included no AL-only or DT-only comparison conditions, so the unique and combined contributions of the two approaches cannot be isolated; the same instructor taught both groups, allowing possible expectancy effects; the SDT constructs were not directly measured; and there was no longitudinal follow-up. Future research should employ factorial and multi-site designs with multiple classes per condition, delayed post-tests, direct mediation analysis using validated need-satisfaction instruments, and mixed-methods evidence.

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Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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