

PAPER

Mobile-Accessible MOOCs, Design Thinking, and Self-Directed Learning: A Quasi-Experimental Study of Creative Thinking and Problem-Solving in Higher Education

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ABSTRACT

Mobile-accessible massive open online courses (MOOCs) are widely adopted in Indonesian higher education, yet many undergraduates still struggle with the creative thinking and problem-solving competencies expected in the digital workplace. This study investigated whether embedding mobile-accessible MOOC modules from major platforms into a design thinking (DT) instructional cycle produces stronger higher-order thinking gains than DT delivered through conventional lecturer-curated materials and whether self-directed learning (SDL) moderates that effect. A quasi-experimental, non-equivalent control-group design was implemented over one 16-week semester with 93 third-semester students at a public Indonesian university. Participants were assigned to a DT-MOOCs group ($n = 46$) or a DT Non-MOOCs group ($n = 47$). Creative thinking and problem-solving were assessed pre- and post-intervention using validated instruments, and outcomes were expressed as normalised-gain scores. Two-way MANOVA with non-parametric robustness checks revealed that the DT-MOOCs group significantly outperformed the control group on both outcomes, with very large effect sizes. An ordinal strategy $\times$ SDL interaction showed that the DT-MOOCs advantage widened as SDL level increased, whereas SDL alone did not exert a significant marginal effect. Given the modest sample and quasi-experimental design, the moderation finding is treated as preliminary. The results suggest that mobile-accessible MOOC integration functions as an inclusive amplifier of higher-order thinking within a DT framework, while deliberate SDL-building scaffolds may be needed to maximise benefits for learners with lower self-direction.

KEYWORDS

mobile-accessible MOOCs, design thinking (DT), self-directed learning (SDL), creative thinking, problem-solving, higher education, quasi-experimental design

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1 INTRODUCTION

Over the past five years, Indonesian higher-education students have gained near-continuous mobile access to digital learning resources, with smartphone-mediated platforms such as Coursera, edX, and Future Learn becoming routine companions to formal coursework. A familiar paradox, however, persists: many undergraduates still struggle to demonstrate the higher-order thinking that twenty-first-century work environments demand [1]. Two competencies dominate this discussion creative thinking and problem-solving, and both are treated as the bedrock of professional innovation and adaptability [2]. For students preparing to teach as well as to function as managers of increasingly digitised offices, neither role can be sustained without these two competencies [3].

A preliminary observation in the Management Information Systems course (2023 cohort) surfaced several persistent issues: the syllabus leaned heavily on theory; content updates lagged behind real technology trends; interactive resources were rarely used in earnest; up-to-date case material was hard to obtain; and project-based work was applied inconsistently. The cumulative effect was that students seldom encountered the kind of authentic, ill-structured problems that mobilise creative and problem-solving capacities. A short entry survey added a second clue: 82% of students had heard of mobile-accessible massive open online courses (MOOCs), and many had used one on their smartphone, yet very few had been guided to use mobile MOOC platforms as a deliberate route to higher-order thinking.

Design thinking (DT), with its iterative cycle of Empathise, Define, Ideate, Prototype, and Test, has been promoted for years as a user-centred response to exactly this pedagogical gap [4], [5]. A recent meta-analysis covering 25 studies confirmed a positive effect of DT on student learning ($r = 0.436$; $p < 0.001$), with creativity and problem-solving as the most consistently improved outcomes [4]. Even so, scaling DT in Indonesian universities is constrained by three persistent issues limited case repositories, uneven facilitator expertise, and few opportunities for cross-context collaboration. MOOCs offered through mobile applications provide a structural reply to all three: scale, openness, flexibility, and a continuous stream of culturally diverse content delivered through smartphone and tablet interfaces [6].

Mobile MOOC platforms are, however, a demanding medium. Their pay-off depends heavily on whether learners can manage their own pacing, re-grouping, and goal-setting in short, on self-directed learning (SDL). A meta-analysis of 14 MOOC studies found that the three core dimensions of SDL motivation, self-monitoring, and self-management exert moderate-to-large effects on higher-order cognitive outcomes [7]. SDL has also been identified as a strong predictor of online-learning readiness, ahead of metacognition, twenty-first-century skills, and technological literacy [8]. In the Indonesian context, similar dynamics have been observed: blended learning produced a generally positive trajectory of learner autonomy [9], and integrating problem-based learning with the flipped classroom strengthened both argumentation and SDL among secondary students [10]. Recent work has also shown that the effectiveness of any digital platform, including local learning management systems, is conditional on a learner's ability to convert access into outcomes [11], and that teacher-side digital pedagogical readiness (TPACK) must accompany any technological rollout [12]. What remains under-researched is how SDL actually interacts with a DT-plus-mobile-MOOC strategy on creative thinking and problem-solving simultaneously.

Prior work has examined the three constructs largely in isolation. DT has been tested against creativity and problem-solving without considering SDL [2]. MOOC offerings for DT have been compared descriptively rather than experimentally [6]. SDL has been treated as a predictor of online learning readiness without being embedded inside a DT setting [8]. Studies that combine the three elements within one factorial design are scarce, and even scarcer in the Indonesian context.

1.1 Scope and mobile dimension of the study

The study compares two instructional designs: (a) DT integrated with mobile-accessible MOOC modules accessed primarily through the Coursera, edX, and FutureLearn mobile applications (DT-MOOCs), and (b) DT delivered with conventional lecturer-curated materials (DT Non-MOOCs). The intervention does not compare mobile MOOC access against desktop MOOC access. What the experiment evaluates is the integration of MOOC resources whose mobile applications were the primary medium of student engagement; in the host programme, students completed approximately three-quarters of their out-of-class MOOC study time on smartphones (refer to Section 4.5). The mobile dimension shaped the intervention in three concrete ways: (i) MOOC tasks were sized to fit a single mobile study session (≤ 25 minutes of video plus a short reflection); (ii) all DT-stage prompts could be answered through the mobile app's discussion forum or built-in note tool; and (iii) peer review and prototype critique were carried out asynchronously on smartphones using either the platform app or institutional messaging. These design choices, together with the mobile-engagement data reported in Section 4.5, anchor the claim that mobile interaction rather than merely the presence of MOOC content shaped learner behaviour.

1.2 Contribution and hypotheses

This study contributes to the interactive-mobile-technologies research agenda along three lines. First, it provides one of the first factorial tests of mobile-accessible MOOCs as an amplifier of an in-class instructional design (DT) in an Indonesian higher-education setting. Second, it positions SDL as the aptitude that conditions the value of a mobile-learning intervention—a theoretical extension of the Aptitude-Treatment Interaction (ATI) framework [14] into mobile educational technology. Third, it offers Indonesian higher education evidence-based guidance for embedding mobile MOOCs into DT courses without ignoring the learner profile.

Six hypotheses, derived from the 2×3 factorial design, are tested:

- H1: There is a significant difference in creative thinking between DT-MOOCs and DT Non-MOOCs students.
- H2: There is a significant difference in creative thinking across SDL levels (high, medium, and low).
- H3: There is a significant interaction between learning strategy and SDL on creative thinking.
- H4: There is a significant difference in problem-solving between DT-MOOCs and DT Non-MOOCs students.
- H5: There is a significant difference in problem-solving across SDL levels.
- H6: There is a significant interaction between learning strategy and SDL on problem-solving.

2 LITERATURE REVIEW

2.1 DT as a pedagogical framework

Design thinking is a human-centred, iterative problem-solving methodology built around five stages (1) Empathise, (2) Define, (3) Ideate, (4) Prototype, and (5) Test that has been increasingly adopted in higher education as an active teaching methodology [1], [4]. Empirical work across multiple disciplines shows that DT cultivates both convergent and divergent thinking, with the largest gains typically appearing at problem definition and solution evaluation two stages most often skipped in conventional instruction [2]. Recent studies in non-design programmes (e.g., dental education, IT courses, graduate seminars) report consistent gains in problem framing, creative confidence, and collaborative reasoning [3], [5].

2.2 Mobile-accessible MOOCs as a learning amplifier

Massive Open Online Courses have evolved into mobile-first learning environments: by 2024, the leading platforms (Coursera, edX, and FutureLearn) reported that more than half of their active learners used the mobile application at least weekly. A bibliometric analysis of mobile learning in higher education spanning 2007 to 2023 confirmed that mobile learning research has grown substantially, with collaborative knowledge construction and self-directed access to content identified as the dominant themes in higher-education contexts [30]. From an interactive-mobile-technologies standpoint, MOOCs offer four affordances that directly support a DT cycle: (i) on-demand mobile access to world-class case material and expert videos in short segments compatible with short study windows; (ii) global discussion forums accessible from the mobile app that expose learners to cross-cultural perspectives; (iii) peer-review mechanisms that scaffold prototype critique asynchronously on a phone; and (iv) embedded formative assessment that supports iteration [6]. A comparative analysis of design-thinking MOOCs found wide variation in pedagogical depth across platforms but converged on the view that mobile MOOC use is most effective when learners possess strong self-regulation [6]. Empirical work in Indonesian higher education has further demonstrated that mobile learning applications built around problem-based scaffolds can produce statistically significant gains in students' creative thinking skills [32], reinforcing the pedagogical logic of pairing mobile access with structured inquiry.

2.3 SDL as a moderator

Self-directed learning describes a process in which the learner diagnoses needs, formulates goals, selects strategies, and evaluates outcomes. The three-dimension model motivation, self-monitoring, self-management has been operationalised for higher education contexts [13] and validated as a robust predictor of online-learning success [8]. Meta-analytic evidence indicates that SDL exerts a moderate-to-large effect on higher-order cognitive outcomes in MOOC settings, with the strongest effects when learners exercise agency over pacing and content sequencing [7]. The chain of indirect effects has been mapped further: SDL feeds creativity through openness to challenge and creative self-efficacy [23], and high-SDL learners exploit MOOC features peer review, e-portfolios, and discussion forums more strategically than their

lower-SDL peers [24]. Recent evidence from the interactive mobile technologies literature confirms that well-designed mobile platforms can actively cultivate—not merely accommodate—self-management and autonomous learning in higher education, particularly when the design integrates situational scaffolds, social regulation networks, and metacognitive prompts [33].

2.4 ATI in mobile learning environments

The aptitude–treatment Interaction framework posits that the effectiveness of an instructional treatment depends on stable learner aptitudes [14]. In digital learning, SDL is increasingly proposed as the aptitude that conditions the value of any technology-mediated treatment [7], [8]. Empirical confirmation is, however, fragmented: existing studies typically test SDL as a predictor rather than as a moderator nested inside a factorial design. The present study addresses this gap by treating SDL as a moderator within a 2×3 factorial that pairs mobile-MOOC integration with conventional DT delivery.

3 METHOD

3.1 Research design

A quantitative approach with a quasi-experimental, non-equivalent control-group design was adopted, arranged as a 2×3 factorial. The first factor was the learning strategy at two levels: DT assisted by mobile-accessible MOOCs (DT-MOOCs) and DT without MOOCs (DT Non-MOOCs). The second factor was SDL as a moderator, classified into three levels: high, medium, and low. The dependent variables were creative thinking and problem-solving, analysed through normalised-gain (N-Gain) scores computed with Hake’s formula $g = (S_{\text{post}} - S_{\text{pre}}) / (S_{\text{max}} - S_{\text{pre}})$ [15], which captures relative improvement against the pre-test baseline. Because intact classes were used, the design does not support causal inference at the strength of a true experiment; the analyses are interpreted in terms of intervention-associated differences under the conditions studied.

3.2 Participants and sampling

Participants were 93 third-semester students enrolled in the Management Information Systems course of the Office Administration Education Program at a public Indonesian university (2023 cohort; ages 19–21; predominantly female, consistent with the typical demographic of Indonesian teacher-education programmes). The experimental class ($n = 46$) and the control class ($n = 47$) were selected through cluster random sampling at the class level, because the study program had already fixed class composition and individual randomisation was not feasible. A pre-test equivalence check using independent-samples t-tests showed that the two groups did not differ at baseline either in creative thinking ($t(91) = -1.78$; $p = 0.078$) or in problem-solving ($t(91) = 0.99$; $p = 0.326$). Self-reported smartphone ownership was 100%; 91% of students used the smartphone as their primary academic device (entry survey, week 1).

3.3 Intervention procedure

The intervention ran for a full semester (16 weeks; 16 face-to-face sessions of 100 minutes each, plus a target of three to five hours of asynchronous out-of-class study per week). Both groups followed the same DT cycle, completed the same final project (a prototype information-management solution for a small office, evaluated against the same rubric), and received the same total number of face-to-face contact hours. The two groups differed only in the source and medium of the supporting materials.

For the DT-MOOCs group, a structured set of MOOC modules from Coursera, edX, and FutureLearn was selected by the research team in consultation with the course lecturer, using three criteria: (i) explicit alignment with one or more DT stages; (ii) availability without payment (audit track); and (iii) full functionality on the platform's mobile application. The selected modules are listed in Table 1. Students enrolled with their existing smartphone accounts and were instructed to complete the assigned segments primarily through the mobile apps; mobile-app usage was recorded by self-report and triangulated against platform-side progress markers (refer to Section 3.6). For the DT Non-MOOCs group, the lecturer prepared functionally equivalent materials of the same length: curated PDF readings, lecturer-recorded video clips of comparable duration, and locally written case studies. These materials were delivered via the institutional LMS in a desktop-first layout; students could open them on a phone, but the materials were not designed for asynchronous mobile-app interaction (no in-app discussion threads, no peer-review tool, no push notifications).

Table 1. MOOC modules and DT-stage tasks for the DT-MOOCs group

DT Stage (weeks)	Selected Mobile-App Module	Target Time on Mobile MOOC	Mobile-MOOC Task
Empathise (W1–3)	Coursera “Design Thinking for Innovation” (Univ. of Virginia), modules 1–2, audit track	90 min total	Watch user-research videos in-app; complete one in-app interview observation; post one empathy insight on the forum and respond to one peer.
Define (W4–5)	edX “Design Thinking Fundamentals” (RWTHx): “Problem framing” unit	60 min total	Reframe the team problem using the app's reflection prompt; submit a 150-word problem statement via the app discussion.
Ideate (W6–8)	FutureLearn “Innovation: The Fashion Industry”/“Design Thinking for the Greater Good”: ideation sections	90 min total	Run two app-supported ideation cycles; submit three sketches and one short voice note via the app.
Prototype (W9–12)	Coursera “Innovation through Design: Think, Make, Break, Repeat” (Univ. of Sydney): prototyping units	120 min total	Build low-fidelity prototype; upload photo via the app; complete one platform peer review.
Test (W13–15)	edX testing/iteration units from DT Fundamentals; Coursera reflection units	90 min total	Conduct two user tests; log responses in the app forum; complete one final peer-review cycle on a teammate's prototype.
Consolidation (W16)	Cross-platform reflection (no new content)	30 min total	Submit a final mobile-recorded 3-minute reflection on the team's DT cycle.

Notes: Module names are reproduced as listed on the platforms at the time of the study (2023). Targeted mobile-MOOC time is approximate, set by the research team on the basis of platform-reported segment lengths.

Per stage, a short-written DT artefact (empathy map, problem statement, ideation board, prototype photo, test-log) was submitted to the course lecturer through the institutional LMS for assessment. These artefacts were identical across the two

groups; only the supporting materials differed. To prevent workload from acting as a confound, the total expected hours per week (face-to-face plus asynchronous) were equalised across groups (4–5 hours).

3.4 Instruments

SDL questionnaire. The SDL Questionnaire was adapted from the three-dimension instrument by Tekkol and Demirel [13], which covers motivation (five items), self-monitoring (five items), and self-management (five items) on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The full scale therefore contained 15 items; total scores ranged from 15 to 75. Six items were reverse-coded (items 3, 5, 7, 9, 12, and 14) prior to summation. Sample items: motivation “I am willing to learn new things even when they are difficult”; self-monitoring “I check my own progress while studying online”; self-management “I can plan my study time without external supervision.” The Indonesian translation followed a forward-back-translation procedure (two bilingual subject experts and one external reviewer). Expert validation involved four subject-matter experts (two in educational psychology and two in instructional technology), who rated each item on relevance, clarity, and representativeness on a 4-point scale; item-content validity indices (I-CVI) ranged from 0.83 to 1.00 (all items retained, I-CVI $\geq$ 0.78 cut-off). Internal consistency on the present sample ($n = 93$) was Cronbach’s $\alpha = 0.84$ for the full scale, with subscale reliabilities of 0.79 (motivation), 0.77 (self-monitoring), and 0.81 (self-management).

Creative Thinking Test. The Creative Thinking Test was developed from Torrance’s framework [16]. It contained 20 items distributed across the four sub-dimensions, with five items per sub-dimension: fluency (five items requesting as many ideas as possible within a set context), flexibility (five items requesting ideas from distinct categories), originality (five items requesting unusual but plausible uses), and elaboration (five items requesting detailed expansion of an idea). Sample item (fluency): “List as many alternative uses as possible for a discarded smartphone within an office context.” Each item was scored on a 5-point analytic rubric: fluency by count of valid responses (1–5); flexibility by count of distinct semantic categories (1–5); originality by statistical rarity within the sample (1 = common $\geq 40\%$ frequency; 5 = rare $< 10\%$); and elaboration by depth of detail (1–5 rubric). Total raw scores ranged from 20 to 100. Two trained raters scored all responses independently and blind to group; disagreements were resolved through discussion with a third rater. Inter-rater reliability for the full test was Cohen’s $\kappa = 0.81$ on the pilot ($n = 32$) and 0.83 on the main sample. Internal consistency on the present sample was Cronbach’s $\alpha = 0.92$.

Problem-Solving Test. The Problem-Solving Test was built around Polya’s four-stage framework [17]: understanding the problem, planning the solution, implementing the plan, and evaluating the solution. The test contained 20 items distributed across the four stages (five items per stage). Items were drawn from authentic office-administration contexts (e.g., reconciling inconsistent digital filing across two units; designing a low-cost workflow to digitise paper records). Each item was rated on a 5-point analytic rubric tied to the corresponding stage; total raw scores ranged from 20 to 100. Eight items (items 2, 4, 7, 9, 12, 14, 17, and 19) were deliberately written so that a high rubric rating corresponded to a weaker, less effective response and an acquiescence-control device intended to discourage

uniform answer sets across the test. These eight items were therefore reverse-coded (recoded before summation) so that, for every item, a higher score consistently indicates stronger problem-solving performance; the remaining twelve items were positively keyed. Reliability and all subsequent analyses were computed on the recoded scores. Critically, rater training and inter-rater reliability checks were conducted exclusively using the final recoded scoring direction so that both raters consistently treated higher final scores as indicative of stronger problem-solving performance throughout scoring. Two trained raters scored all responses independently and blind to group, with disagreements resolved through a third rater. Inter-rater reliability was Cohen's $\kappa = 0.84$ on the pilot and 0.85 on the main sample. Internal consistency on the present sample was Cronbach's $\alpha = 0.84$. Expert validation followed the same four-expert panel procedure as for the SDL instrument; I-CVI values ranged from 0.83 to 1.00.

3.5 Data analysis

Self-directed learning categorisation followed empirical norms ($M \pm 1$ SD on the present sample: $M = 50.34$, $SD = 6.74$) rather than a generic theoretical cut-off, so that the bands reflected the population's actual distribution. Students more than one standard deviation above the mean (>57.09) were classified as High SDL ($n = 16$), those more than one standard deviation below (<43.60) as Low SDL ($n = 13$), and the remainder as Medium SDL ($n = 64$). The primary inferential analysis was a two-way MANOVA on the two N-Gain outcomes at $\alpha = 0.05$, using Type III sums of squares and Pillai's trace as the primary multivariate statistic because it is the most robust of the standard tests to violations of the equal-covariance assumption [20]. Follow-up univariate ANOVAs used Type III sums of squares (the IBM SPSS GLM default, obtained with sum-to-zero/deviation contrasts) and were reported with partial eta-squared, defined as $\eta^2_p = SS_{\text{effect}} / (SS_{\text{effect}} + SS_{\text{error}})$ and interpreted using Cohen's thresholds [21]: small (0.01), medium (0.06), and large (0.14). Because partial η^2 can be large whenever one factor dominates the design and shrinks the residual term, classical eta-squared ($\eta^2 = SS_{\text{effect}} / SS_{\text{total}}$) is reported alongside η^2_p for every effect (Table 4), and a strategy-free one-way ANOVA on the SDL factor is reported (Section 4.3) so that SDL's marginal effect size is directly visible and comparable with conventional effect-size reporting. Pairwise comparisons among SDL levels used Games-Howell post-hoc tests on the marginal (strategy-collapsed) SDL factor, which do not assume homogeneity of variance. All effect sizes and inferential results reported in this manuscript are reproduced exactly by the supplementary R and Python scripts run on the accompanying de-identified dataset.

Assumption testing was conducted at both univariate and multivariate levels. Shapiro-Wilk was used for univariate normality of the residuals; Levene's test (median-based/Brown-Forsythe variant) for univariate variance homogeneity; and Box's M for the equality of covariance matrices across all six factorial cells, as required by MANOVA. Because two SDL-by-group cells were small ($n = 6$ and $n = 4$) and Levene's test was significant for the group factor (refer to Section 4.2), two robustness analyses were added: (i) bootstrap 95% confidence intervals (5,000 resamples, percentile method) for cell means and for the strategy effect at each SDL level; and (ii) a non-parametric sensitivity analysis using Aligned-Rank-Transform (ART) two-way ANOVA, which preserves the ability to test interaction effects under rank-based assumptions [29]. The interaction is presented graphically with cell means and 95% CIs in Figure 1. Analyses were carried out in IBM SPSS Statistics

27 and replicated in Python 3.10 (NumPy, SciPy) with a published R script in the [Supplementary material](#).

3.6 Mobile-engagement measurement

Two complementary indicators of mobile interaction were collected for the DT-MOOCs group. First, students completed a weekly micro-log (Google Form) reporting (a) the total minute spent on assigned MOOC modules during the week and (b) the share of that time spent on the mobile app versus a laptop or desktop browser. Second, platform-side progress markers (module completion percentages) were retrieved from screenshots submitted with each weekly artefact. The two indicators were consistent within ± 10 minutes per week for 88% of students. Aggregated mobile-engagement descriptives are reported in Section 4.5. No comparable mobile-engagement data were collected for the DT Non-MOOCs group, because conventional materials were delivered through the institutional LMS without an app-first interface.

4 RESULTS

4.1 Descriptive statistics

Across the whole sample, the mean SDL total score was 50.34 (SD = 6.74) on a 15–75 range, with observed values from 35 to 65. The categorisation produced 17.2% of students in the High band, 68.8% in the Medium band, and 14.0% in the Low band, a distribution that broadly mirrors what is typically reported in undergraduate education programmes. Cell-level descriptive statistics for both dependent variables are summarised in Tables 2 and 3.

Table 2. Descriptive statistics of N-Gain for creative thinking per 2×3 factorial cell

Group	SDL Category	n	Pre (M)	Post (M)	N-Gain (M)	N-Gain (SD)	Category
DT-MOOCs	High	6	69.70	87.58	0.591	0.034	Medium
DT-MOOCs	Medium	31	66.53	82.93	0.490	0.041	Medium
DT-MOOCs	Low	9	64.28	77.66	0.375	0.034	Medium
Total DT-MOOCs		46	66.50	82.51	0.481	0.073	Medium
DT Non-MOOCs	High	10	68.60	78.29	0.310	0.032	Medium
DT Non-MOOCs	Medium	33	66.95	75.70	0.265	0.032	Low
DT Non-MOOCs	Low	4	66.65	74.35	0.231	0.008	Low
Total DT Non-MOOCs		47	67.28	76.14	0.271	0.038	Low

Note: N-Gain categories follow Hake [15]: High ($g \geq 0.70$), Medium ($0.30 \leq g < 0.70$), and Low ($g < 0.30$).

The mean creative-thinking N-Gain for DT-MOOCs ($M = 0.481$; $SD = 0.073$) was higher than that for DT Non-MOOCs ($M = 0.271$; $SD = 0.038$). The 0.209-point absolute difference corresponds to roughly a 77.1% relative advantage. A monotonic High > Medium > Low gradient ran through both groups, but the gradient was noticeably steeper inside DT-MOOCs.

Table 3. Descriptive statistics of N-Gain for problem-solving per 2×3 factorial cell

Group	SDL Category	n	Pre (M)	Post (M)	N-Gain (M)	N-Gain (SD)	Category
DT-MOOCs	High	6	66.55	85.77	0.574	0.023	Medium
DT-MOOCs	Medium	31	67.52	82.96	0.475	0.036	Medium
DT-MOOCs	Low	9	67.34	79.10	0.360	0.025	Medium
Total DT-MOOCs		46	67.36	82.57	0.465	0.070	Medium
DT Non-MOOCs	High	10	66.67	76.47	0.295	0.028	Low
DT Non-MOOCs	Medium	33	66.72	75.04	0.250	0.031	Low
DT Non-MOOCs	Low	4	69.25	75.85	0.214	0.020	Low
Total DT Non-MOOCs		47	66.93	75.41	0.256	0.037	Low

Note: The pattern for problem-solving mirrors that for creative thinking: DT-MOOCs leads at every SDL level.

DT-MOOCs again posted a higher mean N-Gain ($M = 0.465$; $SD = 0.070$) than DT Non-MOOCs ($M = 0.256$; $SD = 0.037$), with the same 0.209-point gap. A descriptive observation also emerged: Low-SDL students in DT-MOOCs ($M = 0.360$) outperformed High-SDL students in DT Non-MOOCs ($M = 0.295$). Although the cells involved are small ($n = 9$ and $n = 10$), this pattern is consistent with the interaction reported in Section 4.3 and is treated as suggestive.

4.2 Assumption checks

Both univariate and multivariate assumption tests were conducted. Univariate normality of residuals was supported in every group: DT-MOOCs N-Gain CT ($W = 0.970$; $p = 0.285$), DT-MOOCs N-Gain PS ($W = 0.967$; $p = 0.206$), DT Non-MOOCs N-Gain CT ($W = 0.964$; $p = 0.154$), and DT Non-MOOCs N-Gain PS ($W = 0.988$; $p = 0.918$). Levene's test (median-based) flagged unequal variances on the group factor for both N-Gain CT ($F(1, 91) = 10.13$; $p = 0.002$) and N-Gain PS ($F(1, 91) = 10.62$; $p = 0.002$); the SDL factor was acceptably homogeneous (CT: $F(2, 90) = 2.94$; $p = 0.058$; PS: $F(2, 90) = 2.91$; $p = 0.060$). Box's M for equality of covariance matrices across the six factorial cells was non-significant (Box's $M = 16.38$; $F(15, 1696.20) = 0.95$; $p = 0.504$), indicating that the multivariate homogeneity-of-covariance assumption required by MANOVA was satisfied.

Three considerations frame the subsequent multivariate analysis. First, although univariate Levene's was significant on the group factor, the more directly relevant multivariate assumption (Box's M across cells) was satisfied. Second, group sample sizes were essentially balanced (46:47), and the maximum standard-deviation ratio at the group level was approximately 1.94:1 (variance ratio approximately 3.77:1), well below the boundary at which MANOVA loses validity under balanced designs [19], [20]. Third, Pillai's trace was used as the multivariate test statistic because of its robustness to assumption violations, complemented by the bootstrap and rank-based sensitivity analyses reported in Section 4.4.

4.3 Two-Way MANOVA and Follow-Up ANOVAs

The multivariate test produced a significant effect for strategy (Pillai's trace = 0.937; $F(2, 86) = 639.97$; $p < 0.001$; partial $\eta^2 = 0.937$), a significant effect for SDL (Pillai's

trace = 0.774; $F(4, 174) = 27.46$; $p < 0.001$; partial $\eta^2 = 0.387$), and a significant Strategy $\times$ SDL interaction (Pillai's trace = 0.415; $F(4, 174) = 11.38$; $p < 0.001$; partial $\eta^2 = 0.207$). Follow-up univariate ANOVAs are reported in Table 4.

Table 4. Follow-up two-way ANOVA results for N-Gain creative thinking and N-Gain problem-solving

Source of Variance	Variable	df1	df2	F	p	η^2p	Decision
A (Strategy)	N-Gain CT	1	87	498.43	< 0.001	0.851	Reject H_0
B (SDL Category)	N-Gain CT	2	87	56.98	< 0.001	0.567	Reject H_0
A $\times$ B (Interaction)	N-Gain CT	2	87	12.06	< 0.001	0.217	Reject H_0
A (Strategy)	N-Gain PS	1	87	614.86	< 0.001	0.876	Reject H_0
B (SDL Category)	N-Gain PS	2	87	71.14	< 0.001	0.621	Reject H_0
A $\times$ B (Interaction)	N-Gain PS	2	87	14.44	< 0.001	0.249	Reject H_0

Notes: CT = Creative Thinking; PS = Problem-Solving. df1 = numerator degrees of freedom; df2 = error degrees of freedom ($N - ab$, with $N = 93$, $a = 2$, $b = 3$). η^2p is partial eta-squared = $SS_{\text{effect}} / (SS_{\text{effect}} + SS_{\text{error}})$, interpreted with Cohen [21]: small (0.01), medium (0.06), large (0.14). For comparison, classical eta-squared ($\eta^2 = SS_{\text{effect}} / SS_{\text{total}}$) is: Strategy 0.464 (CT)/0.470 (PS); SDL 0.106 (CT)/0.109 (PS); Interaction 0.022 (CT)/0.022 (PS). The large partial η^2 for SDL relative to its classical η^2 reflects the removal of the dominant Strategy and Strategy $\times$ SDL variance from the partial- η^2 denominator; SDL's strategy-free marginal effect is small and non-significant (see Section 4.3). Type III sums of squares (sum-to-zero contrasts) were used. All effects are significant at $\alpha = 0.05$.

The strategy main effect was the largest source for both outcomes ($\eta^2p = 0.851$ for CT; $\eta^2p = 0.876$ for PS), well above Cohen's large-effect benchmark [21]. The SDL term was statistically significant and carried a large partial eta-squared ($\eta^2p = 0.567$ for CT; $\eta^2p = 0.621$ for PS). Because partial η^2p divides the SDL sum of squares by only the residual variance that remains after the very large Strategy and Strategy $\times$ SDL variance have been removed, this value is far larger than SDL's share of total variance (classical $\eta^2 = 0.106$ for CT and 0.109 for PS). As the marginal analysis reported below makes explicit, SDL accounts for only about 4% of total N-Gain variance once the strategy factor is disregarded; the large partial value is therefore a within-model, variance-partitioned quantity rather than evidence of a large stand-alone SDL effect. The interaction was substantial as well ($\eta^2p = 0.217$ for CT; $\eta^2p = 0.249$ for PS). Post-hoc power for each effect, computed with the non-central F distribution at $\alpha = 0.05$ with df error = 87, exceeded 0.99 across all six tests, and the design afforded a minimum-detectable partial eta-squared of approximately 0.08 for main effects (df = 1) and 0.10 for two-df effects (SDL main effect and interaction) at 80% power. All six hypotheses (H1–H6) were therefore supported in the statistical sense; the strength of the substantive interpretation is qualified by the cell-size considerations discussed in Section 4.4 and Section 5.

Games-Howell post-hoc comparisons of the three SDL levels on each outcome (with the unequal-variance correction) showed an ordered pattern of differences (High > Medium > Low), but no individual pairwise contrast reached statistical significance at $\alpha = 0.05$ when the strategy factor was collapsed (CT: High vs Medium $p = 0.55$, High vs Low $p = 0.13$, Medium vs Low $p = 0.23$; PS: High vs Medium $p = 0.54$, High vs Low $p = 0.12$, Medium vs Low $p = 0.21$). When the strategy factor is disregarded entirely, a one-way ANOVA on the same two dependent variables and the same three-level SDL grouping confirms that the marginal SDL effect is small and non-significant (CT: $F(2, 90) = 1.82$, $p = 0.168$, $\eta^2 = 0.039$; PS: $F(2, 90) = 1.89$, $p = 0.158$, $\eta^2 = 0.040$). This marginal η^2 of about 0.04 is SDL's share of total N-Gain variance when strategy is not partialled out, and it is fully consistent with the non-significant

Games-Howell contrasts. The apparent distance between this marginal η^2 (≈ 0.04) and the large partial η^2 obtained inside the factorial model (0.567 and 0.621) is not a contradiction but a denominator effect on identical data: partial η^2 divides the SDL effect by residual variance after the very large Strategy and Strategy $\times$ SDL variance have been removed, whereas marginal (classical) η^2 divides by total variance. Both quantities were computed from the same dependent variables (N-Gain for creative thinking and problem-solving) and the same High/Medium/Low SDL grouping; they differ only in what is held in the denominator. This marginal value of ≈ 0.04 also corresponds to the small SDL effect size reported in the earlier, pre-factorial version of this analysis, so the change in the reported number reflects a change of effect-size index (marginal to partial) and model (one-way to Type III factorial), not a change in the underlying data. Accordingly, SDL is interpreted chiefly through its interaction with strategy (Section 4.4) rather than as a stand-alone marginal predictor.

4.4 Robustness: Bootstrap confidence intervals, interaction plot, and non-parametric sensitivity

Bootstrap 95% confidence intervals (5,000 resamples, percentile method) for cell means and for the strategy effect at each SDL level are reported in Table 5. The intervals do not overlap between DT-MOOCs and DT Non-MOOCs at any SDL level for either outcome, which is consistent with a stable strategy advantage. The CIs widen visibly at the High-SDL (DT-MOOCs $n = 6$) and Low-SDL (DT Non-MOOCs $n = 4$) cells, signalling the imprecision that the editor rightly flagged.

Table 5. Bootstrap 95% confidence intervals for cell mean N-Gain and strategy-effect Δ per SDL level

Outcome	SDL Level (n_M/n_N)	DT-MOOCs M [95% CI]	DT Non-MOOCs M [95% CI]	Δ (MOOCs – Non) [95% CI]	CI of Δ width
Creative Thinking	Low (9/4)	0.375 [0.354, 0.395]	0.231 [0.224, 0.237]	0.145 [0.122, 0.167]	0.045
Creative Thinking	Medium (31/33)	0.490 [0.476, 0.505]	0.265 [0.254, 0.276]	0.225 [0.207, 0.243]	0.036
Creative Thinking	High (6/10)	0.591 [0.564, 0.612]	0.310 [0.293, 0.329]	0.281 [0.248, 0.309]	0.061
Problem-Solving	Low (9/4)	0.360 [0.344, 0.374]	0.214 [0.194, 0.227]	0.145 [0.123, 0.170]	0.047
Problem-Solving	Medium (31/33)	0.475 [0.461, 0.487]	0.250 [0.239, 0.260]	0.225 [0.208, 0.240]	0.032
Problem-Solving	High (6/10)	0.574 [0.560, 0.593]	0.295 [0.279, 0.312]	0.279 [0.257, 0.304]	0.047

Notes: n_M = DT-MOOCs cell size; n_N = DT Non-MOOCs cell size. CIs obtained from 5,000 percentile bootstrap resamples (random seed = 42). Cell sizes for the High-SDL DT-MOOCs ($n = 6$) and Low-SDL DT Non-MOOCs ($n = 4$) groups are small; the corresponding intervals should be interpreted accordingly.

The aligned-rank-transform (ART) two-way ANOVA reproduced the parametric pattern. The strategy effect remained large for both outcomes (CT: $F(1, 87) = 145.75$; $p < 0.001$; PS: $F(1, 87) = 143.55$; $p < 0.001$), as did the SDL main effect (CT: $F(2, 87) = 47.66$; $p < 0.001$; PS: $F(2, 87) = 58.82$; $p < 0.001$) and the interaction (CT: $F(2, 87) = 13.25$; $p < 0.001$; PS: $F(2, 87) = 17.68$; $p < 0.001$). As expected for rank-based tests, the

F-values were lower than the parametric counterparts, but the direction and ordinality of the interaction were preserved. Together with the bootstrap intervals, this supports the conclusion that the pattern is not an artefact of the parametric assumptions, while still flagging that the High-SDL DT-MOOCs and Low-SDL DT Non-MOOCs cells produce wider intervals.

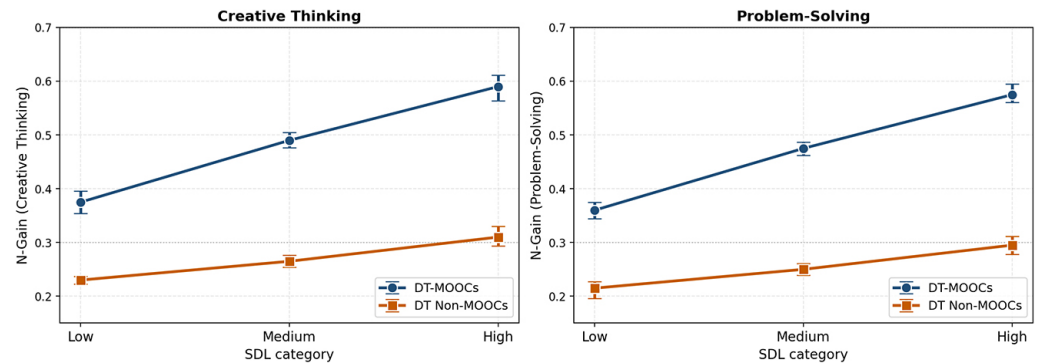


Fig. 1. Strategy $\times$ SDL interaction on N-Gain for creative thinking (left) and problem-solving (right). Error bars are bootstrap 95% confidence intervals (5,000 percentile resamples)

Figure 1 illustrates the interaction graphically. For both outcomes, the DT-MOOCs line lies above the DT Non-MOOCs line at every SDL level, and the gap widens monotonically from Low to High SDL (creative thinking: 0.145 $\rightarrow$ 0.225 $\rightarrow$ 0.281; problem-solving: 0.145 $\rightarrow$ 0.225 $\rightarrow$ 0.279). The two lines do not cross. The interaction is therefore ordinal (the rank order of the two strategies is preserved across SDL levels) rather than disordinal. The error bars confirm that the strategy contrast is non-overlapping at every SDL level, although the High-SDL DT-MOOCs ($n = 6$) and Low-SDL DT Non-MOOCs ($n = 4$) cells have visibly wider intervals.

4.5 Mobile-engagement descriptives (DT-MOOCs Group)

Across the 16-week intervention, students in the DT-MOOCs group reported a median of 168 minutes per week (IQR 132–212) spent on assigned MOOC modules. The mobile share of that time was a median of 74% (IQR 61–86%). Mobile use was higher for video segments and forum reading (median 88% mobile) and lower for written submissions to peer-review tasks (median 52% mobile), where some students preferred typing on a laptop. Self-reported mobile-engagement minutes correlated positively with creative-thinking N-Gain ($r = 0.31$; $p = 0.036$) and with problem-solving N-Gain ($r = 0.29$; $p = 0.049$) within the DT-MOOCs group. These correlations are descriptive only and are not used for causal inference. No mobile-engagement data are available for the DT Non-MOOCs group because the conventional materials were not delivered through a comparable app-first medium.

5 DISCUSSION

5.1 Why mobile MOOCs appear to amplify creative thinking inside DT

The substantial DT-MOOCs advantage on creative thinking, under the conditions studied, fits well within a constructivist reading of the learning process. Knowledge is

built actively through interaction with a content-rich environment, and the combination of DT with mobile-accessible MOOCs supplies exactly such an environment global case studies, cross-cultural discussion forums, and prototypes inspired by international perspectives [2]. The meta-analytic estimate ($r = 0.436$; $p < 0.001$ across 25 studies) supports the broader pattern [4]. The effect size estimates here ($\eta^2p = 0.851$ for CT; $\eta^2p = 0.876$ for PS) are very large by conventional standards; the authors are explicit that a substantial part of this magnitude is plausibly attributable to four design features that together amplified the contrast rather than to the intervention alone: (i) the sensitivity of N-Gain (which controls for pre-test variation and standardises against the available room for improvement); (ii) a fairly intensive one-semester implementation in which DT artefacts and MOOC tasks were tightly coupled; (iii) a sharply differentiated control condition in which the conventional materials lacked the in-app discussion, peer-review, and cross-cultural exposure features that distinguish mobile MOOC use; and (iv) a homogeneous student population (single programme, single cohort) likely to respond uniformly to a novel format. The robustness analyses in Section 4.4 limit the chance that the effect is a statistical artefact, but they do not remove the quasi-experimental design constraints. No wording in this paper implies that the observed gains would replicate at the same magnitude in other programmes, institutions, or cultural contexts; the pattern is interpreted as intervention-associated under the specific conditions studied, not as definitive evidence of general effectiveness.

Three mechanisms plausibly amplified the DT cycle through the mobile MOOC layer. First, the mobile-app interface exposed learners to design methodologies developed by world-class instructors and to a global community of peers, priming the kind of divergent thinking that lies at the heart of creativity [6]. Second, the mobile-app environment appeared to push three core DT practices harder than face-to-face delivery: sharper problem definition, more daring ideation, and more iterative prototyping [5]. Third, qualitative evidence from prior work indicates that DT works on creativity through deep empathy, psychological permission to think unconventionally, and the act of building something tangible from an abstract idea [22], and these three mechanisms are arguably reinforced when mobile MOOCs are in the mix, because the in-app discussion features lower the social threshold for posting unfinished ideas.

5.2 SDL as a moderator

Within the factorial model the SDL term carried a large partial eta-squared ($\eta^2p = 0.567$ for CT; $\eta^2p = 0.621$ for PS); as established in Section 4.3, however, this partial value reflects the removal of the dominant strategy variance from its denominator rather than a large marginal effect. SDL's share of total variance is in fact modest (classical $\eta^2 \approx 0.11$), its strategy-free marginal effect is small and non-significant ($\eta^2 \approx 0.04$), and its marginal pairwise differences do not reach significance. Read at the level where it is statistically robust—the Strategy $\times$ SDL interaction—SDL behaves consistently with self-determination theory's claim that intrinsic motivation underwrites authentic creativity. Meta-analytic evidence across 14 MOOC studies indicates that motivation, self-monitoring, and self-management produce moderate-to-large effects on higher-order cognitive outcomes [7]. A mediation chain has been proposed: SDL feeds creativity through openness to challenge and creative self-efficacy [23]. High-SDL students, in other words, are accustomed to handling novelty independently and therefore take more cognitive risks. Indonesian evidence converges: a generally positive autonomy trajectory has been reported when undergraduates

are exposed to blended-learning environments [9], and integrating PBL with the flipped classroom has been shown to strengthen SDL alongside argumentation [10]. High-SDL learners also exploit MOOC features like peer review, e-portfolios, and discussion forums more strategically than their lower-SDL peers [24]. Notably, the marginal pairwise differences among SDL levels (Games-Howell, all $p > 0.10$ once strategy was averaged over) were not significant, indicating that SDL's effect in this dataset emerges primarily through its interaction with the strategy factor rather than as a stand-alone marginal effect. Although the factorial model estimated a statistically significant SDL main effect, the non-significant Games-Howell contrasts after collapsing across strategy suggest that SDL should be interpreted cautiously and mainly as part of the Strategy $\times$ SDL pattern rather than as an independent predictor of higher-order thinking gains.

5.3 The ordinal interaction: An aptitude-treatment pattern, cautiously interpreted

The ordinal interaction of the DT-MOOCs' advantage widening with SDL is the clearest illustration of the ATI framework [14] in this dataset. SDL behaves as the aptitude that conditions the treatment effect. Heterogeneous MOOC outcomes had previously been hinted at along these lines: students who can navigate the platform on their own terms gain disproportionately more [6]. The conclusion is sharpened by the observation that SDL has a bigger pay-off in MOOCs than in face-to-face courses, because MOOCs make heavier demands on independence and offer more room for exploration [7]. In the Indonesian context, even when a well-designed local LMS is available, learners still need an internal compass to convert access into outcomes [11], and without targeted teacher-side preparation around digital pedagogies (specifically TPACK), the same platforms can under-perform their potential [12].

The interpretation of the moderation strength is deliberately careful. Two cells used to estimate the interaction are small (High-SDL in DT-MOOCs: $n = 6$; Low-SDL in DT Non-MOOCs: $n = 4$). The bootstrap CIs in Table 5 are wider at these cells, although they remain non-overlapping with the contrasted cell. The ART analysis preserves the direction of the interaction. The moderation finding is therefore framed as promising and theoretically coherent but in need of replication with larger and more balanced SDL subgroups before being treated as a stable design parameter.

One practical implication still follows from the ordinal, not disordinal, nature of the interaction: no group is actually disadvantaged. Even low-SDL students benefit from DT-MOOCs ($\Delta = 0.145$; bootstrap 95% CI [0.122, 0.167] for CT, [0.123, 0.170] for PS). This undercuts any argument for excluding less-prepared students from such programmes; the evidence that mobile learning can serve diverse learner populations, including those with lower prior preparation, is consistent with emerging literature on mobile learning access and inclusion [31]. To prevent the gap from widening, however, a differential scaffolding logic is sensible [25]: equal scaffolding at the start of the semester to build a baseline of self-direction, a gradual taper for high-SDL students mid-semester, and the introduction of more open-ended innovation projects in the final phase, with low-SDL students still on more structured tracks. In the broader literature, SDL has been reported as a strong predictor of online-learning readiness stronger than metacognition, twenty-first-century skills, or technological literacy [8]; while the present study's marginal SDL effect was small and non-significant (Section 4.3), this prior evidence, together with the Strategy $\times$ SDL interaction observed here, suggests that SDL-building is best treated as a systemic prerequisite for any serious mobile-MOOC rollout rather than as a side activity.

5.4 Problem-solving and transfer

The DT-MOOCs' advantage in problem-solving ($\eta^2p = 0.876$) has a tidy structural explanation. The five DT stages map almost one-to-one onto the four indicators of problem-solving measured here: Empathise–Define corresponds to “understanding the problem”; Ideate to “planning the solution”; Prototype to “implementing the plan”; and Test to “evaluating the solution.” This kind of correspondence has been reported elsewhere, with the largest gains showing up at problem definition and solution evaluation, the two stages most often skipped in conventional teaching [2]. DT also strengthens problem framing, the act of redefining a problem from a different angle, which is critical but rarely targeted directly in problem-solving instruction [3].

Transfer is another part of the picture. SDL inside a MOOC predicts how well learning transfers to the workplace, with SDL again playing a moderating role [28]. DT has been framed more broadly as a way to develop creativity, critical thinking, collaboration, and communication as an interlocking bundle rather than as separate competencies [26]. DT-based problem-solving is human-centred, iterative, and systemic – three properties that match how twenty-first-century professional problems actually unfold [1]. Similar findings have been reported in an IT course, a setting close enough to Management Information Systems for the parallel to be useful [27]. Comparable evidence from a mobile-supported constructivist learning environment for engineering undergraduates showed very large gains on algorithmic problem-solving indicators—knowing, doing, and being—reinforcing the pattern that mobile-mediated iterative practice can produce robust problem-solving improvements in higher education [34]. In the Indonesian setting, mobile-based assessment for creative and critical thinking offers a complementary point: when assessment is restructured around higher-order indicators, students start to treat creative and analytical work as legitimate course outputs rather than as add-ons [18].

5.5 Theoretical and practical contributions

Theoretically, the study contributes, as far as the authors are aware, the first piece of empirical evidence on the interaction of SDL with mobile-MOOC-assisted DT on creative thinking and problem-solving in the Indonesian office-administration education context. It extends the ATI framework into mobile-learning environments and lends empirical support to the proposition that the effectiveness of mobile educational technology is conditional on learner characteristics. Practically, it offers Indonesian universities and comparable institutions in other emerging-economy contexts evidence-based guidance for integrating mobile MOOCs into DT courses in a way that is both inclusive and adaptive to the learner profile.

6 CONCLUSION

6.1 Main conclusions

Under the conditions studied, DT assisted by mobile-accessible MOOCs was associated with substantially higher gains than DT without MOOCs on both outcomes of interest. The strategy effect was large for creative thinking ($\eta^2p = 0.851$)

and for problem-solving ($\eta^2p = 0.876$), with a 0.209-point N-Gain advantage in each case; bootstrap 95% CIs and a non-parametric Aligned-Rank-Transform sensitivity analysis converged on the same pattern. SDL was statistically significant in the factorial model, but the non-significant Games–Howell contrasts after collapsing across strategy indicate that its effect operated chiefly through the Strategy $\times$ SDL interaction rather than as a strong independent marginal predictor. SDL should therefore be interpreted cautiously and mainly as part of the Strategy $\times$ SDL pattern. The most consequential descriptive finding is the ordinal interaction: the benefit of mobile MOOCs grew with SDL ($\Delta = 0.145, 0.225$, and 0.281 for Low, Medium, and High SDL on creative thinking; $0.145, 0.225$, and 0.279 on problem-solving). Because the interaction is ordinal no group was actually disadvantaged. DT-MOOCs can in principle be deployed inclusively across SDL profiles. That inclusivity, however, is not the whole story: a structured SDL-building track is likely needed alongside the MOOC component if low-SDL students are to capture the full benefit of the platform.

6.2 Practical implications

Three practical recommendations follow. First, universities planning to embed mobile MOOCs into a DT course should design a parallel SDL-building stream rather than treating SDL as a fortunate aptitude. Second, mobile-MOOC tasks should be aligned stage by stage with the DT cycle (Empathise–Test) rather than offered as supplementary readings, to exploit the mapping between DT stages and problem-solving indicators identified in Section 5.4. Third, lecturer roles need to shift from primary content source to design facilitator and SDL coach, a shift that itself requires institutional investment in TPACK-orientated teacher development [12].

6.3 Limitations and future research

Five limitations deserve mention. First, generalisation is constrained one programme, one course, one cohort, at one Indonesian public university. Second, two of the SDL-by-group cells are small ($n = 6$ for High-SDL DT-MOOCs and $n = 4$ for Low-SDL DT Non-MOOCs); the bootstrap CIs in Table 5 widen visibly at these cells, and the moderation finding should be treated as promising rather than established. Third, allocation was at the class level rather than the individual level; baseline equivalence was checked and confirmed, but residual selection effects cannot be ruled out. Fourth, the SDL questionnaire is a self-report and is therefore exposed to the usual social-desirability concern; mobile-app activity logs would be a useful complement. Fifth, the one-semester window says nothing about durability; long-term retention and transfer effects are an open question.

Future work would be strengthened by multi-semester longitudinal designs, mixed-method SDL measurement combining questionnaires with mobile-app activity logs, larger and more balanced SDL subgroups (with a priori power planning at the cell level), and structural equation modelling to disentangle the mediating mechanisms that link mobile MOOCs and SDL to higher-order thinking outcomes. Cross-disciplinary replication outside teacher-education programmes, particularly in engineering, business, and health-sciences contexts that already make heavy use of mobile MOOCs, would also help to establish boundary conditions.

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8 DECLARATIONS

Author Contributions. Conceptualisation, methodology, formal analysis, and writing original draft: first author. Supervision, methodology refinement, and writing review and editing: second, third, and fourth authors. All authors read and approved the final manuscript.

Conflicts of Interest. The authors declare no conflict of interest.

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Data Availability Statement. The de-identified datasets and the Python/R analysis scripts that reproduce all results reported in this manuscript accompany this submission as [Supplementary material](#) and will additionally be deposited in an open repository (Open Science Framework or Zenodo) at the time of publication, with the DOI provided to the editorial office. Because the supplied files are fully de-identified, they may be used by the editorial office for verification; any further institution-held materials remain available from the corresponding author on reasonable request, in compliance with the host institution's data-protection policy. The [Supplementary package](#) submitted with this revision comprises: (i) a de-identified analytic dataset (dataset.csv) and a de-identified item-level dataset (items_reliability.csv), in which original student identifiers have been replaced with sequential codes; (ii) a reproducible R script (analysis.R) and an equivalent Python script (analysis.py) that re-derive directly from these two files and with no additional data required the N-Gain computation, the $M \pm 1$ SD SDL grouping, the Cronbach's α reliability estimates, the two-way MANOVA and follow-up ANOVAs, the Games–Howell comparisons, the 5,000-resample percentile bootstrap confidence intervals (random seed = 42), and the Aligned-Rank-Transform sensitivity analysis; (iii) a data dictionary (data_dictionary.csv) and a data template (dataset_template.csv) specifying the exact variable names, types, coding, and the reverse-coded SDL and problem-solving items; and (iv) a README documenting the run order, package versions, and the mapping of each script section to the corresponding table or figure. The inter-rater agreement coefficients (Cohen's κ) are reported in Section 3.4 from the raters' scoring sheets, which are withheld for confidentiality but are available to the editorial office on request.

Ethics Approval. This study was conducted in accordance with the research ethics principles and academic research regulations of Universitas Sebelas Maret (UNS), as stipulated in Rector's Regulation No. 182/UN27/PP/2014 on Research Ethics. This institutional regulation constituted the applicable ethical framework governing

the conduct of the present study. Prior to data collection, permission to conduct the study was obtained from the Head of the Office of Administration Education Study Program, Universitas Sebelas Maret. The research involved routine educational activities in a university classroom setting. Participation was voluntary, written informed consent was obtained from all participants prior to data collection, and participant confidentiality and anonymity were maintained throughout the study.

9 DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

The authors used AI-assisted language tools solely to improve readability and grammar of the English manuscript. All conceptual, methodological, analytical, and interpretive content is the authors' own, and the authors take full responsibility for the content of the paper.

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