

Moolang Virtual Class Platform: Economic Learning Outcomes and Implication for Entrepreneurship Education

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ABSTRACT

Objective: This study evaluates the effectiveness of the Moolang virtual learning platform in improving economic learning outcomes and examines its relevance to economic and entrepreneurship education amid Indonesia's shifting digital learning habits. **Method:** A four-phase quasi-experimental design compared an experimental class ($n = 30$, Universitas Negeri Malang) using Moolang with a control class ($n = 30$, State University of Surabaya) receiving conventional instruction, under balanced internet connectivity conditions (50% strong, 50% weak, self-reported). Learning outcomes on demand-supply economic concepts were assessed at the end of each phase and analyzed using a mixed-design (split-plot) ANOVA with Group (experimental vs. control) as the between-subjects factor and Phase (1-4) as the within-subjects factor. **Results:** The experimental class significantly outperformed the control class in Phase 2 ($p = .038$, $d = 0.55$), Phase 3 ($p < .001$, $d = 1.85$) and Phase 4 ($p = .007$, $d = 0.73$), with no difference at Phase 1 baseline ($p = .568$, $d = 0.15$). The mixed ANOVA showed a significant Group main effect, $F(1,58) = 34.37$, $p < .001$ and a significant Group $\times$ Phase interaction, $F(3,174) = 5.52$, $p = .001$ (Greenhouse-Geisser corrected $p = .003$ following a significant Mauchly's test), while the Phase main effect alone was not significant, $F(3,174) = 1.29$, $p = .278$. **Novelty:** Unlike prior evaluations that treat virtual classrooms as a generic phenomenon and analyze repeated-measures data with independent-samples ANOVA, this study applies a mixed-design ANOVA appropriate to the repeated-phase structure of the data and situates platform effectiveness within economics-specific case content (price-mechanism reasoning and implicit opportunity-cost trade-offs) rather than treating entrepreneurship relevance as an unexamined extension.

INTRODUCTION

In the Indonesian economic education landscape, the incorporation of virtual classroom platforms has ushered in a shift in how pedagogical content is delivered. The limited movement space during 2019-2020 accelerated the adoption of digital learning across Indonesian institutions, encouraging virtual classroom platforms as a methodology for delivering economics instruction rather than merely as a substitute for classroom attendance (Siron, 2020). Meta analysis across thirty studies likewise found small but the positive effects of digital platforms on learning outcomes relative to traditional classrooms (Cao, 2023; Alshammary & Alhalafawy, 2023).

Lecturer-based instruction of core economics concepts such as demand and supply often produces procedural familiarity. Students can recite the law of demand without producing durable conceptual understanding or the applied reasoning needed to analyse real market events. This gap between procedural recall and applied economic reasoning is a persistent pedagogical problem rather than a peripheral one (Narmaditya, 2018). Technology-supported on case-based learning has been proposed as a response to

precisely this problem. The premise here is that reasoning through authentic market scenarios, rather than memorizing definitions about “what builds transferable economic understanding?”.

Siron (2020) found that the adoption of e-learning in Indonesia during the pandemic was shaped by perceived ease of use (consistent with the framework proposed by Venkatesh et al., 2003) and perceived enjoyment, both of which remain critical for students transitioning away from traditional lecture settings. Daroin and Andriani (2021) add that economic learning for Generation Z benefits from digital, practical and visually engaging methods rather than passive delivery. Yet a platform's popularity with students does not by itself indicate pedagogical value; institutions still need frameworks for judging whether a given tool actually strengthens economic reasoning.

Rapanta et al. (2021) argue that technology integration must be anchored in a technology first mindset toward pedagogically grounded decisions about when digital tools genuinely serve learning outcomes. Bond et al. (2024) systematic literature review shows that learning analytics can reveal engagement patterns that conventional log data measures leave invisible to instructors. Together these perspectives suggest that evaluating a virtual classroom platform requires more than measuring usage; it requires evidence that the platform changes what students actually learn (Lacka & Wong, 2021).

A rigorous evaluation of a virtual classroom platform typically spans usability, accessibility, engagement and learning outcomes. Picciano (2017) stresses that alignment between interactivity, content and assessment is what separates an effective online environment from an ornamental one. Garrison and Kanuka (2004) and Armah et al. (2023) offer the Community of Inquiry framework, which treats cognitive, social and instructional presence as jointly necessary for meaningful online learning. Siemens and Gašević (2017) argue that learning analytics and educational data mining should feed back into real-time instructional adjustment rather than serve only as retrospective reporting.

Technological competence is a further precondition for these frameworks to matter in practice. Wardoyo (2021) found that technological knowledge and game-based learning jointly support student achievement, implying that a platform's benefits are conditional on both students' and teachers' readiness to use it well. This readiness gap is documented directly among economics educators: Sojanah et al. (2021) surveyed 217 economics teachers in the Greater Bandung area and found that teaching experience, training and self-efficacy all predict Technological Pedagogical and Content Knowledge (TPACK), and that overall TPACK levels among economics teachers remained low. Scherer et al. (2020) found that structured strategies such as using teacher educators as role models and authentic technology experiences can meaningfully strengthen preservice teachers TPACK. This is suggesting the low levels documented among practicing economics teachers are not fixed but responsive to deliberate preparation. Kholifaturrohman and Mulasiwi (2021) similarly found that Technological Pedagogical Knowledge was the weakest TPACK component among economics and accounting teachers in Central Java and Krisnaresanti et al. (2023) reported that pre-service economics teachers at Universitas Jenderal Soedirman scored lowest specifically on Content Knowledge despite adequate technological skill. This TPACK gap has also been happening in other countries (Yue et al., 2024). These findings matter for the present study because Moolang's effectiveness cannot be separated from the instructional design decisions made by the teachers who operate it.

Student-side readiness follows a parallel pattern. Adha (2022) found that self-regulated learning and digital literacy jointly predict economics learning outcomes through self-efficacy, while Syamiya et al. (2022) showed that digital literacy predicts online learning outcomes specifically in macroeconomics coursework, with the relationship moderated by gender and family socio-economic status (Islamia & Arif, 2024). Indonesia's broader digital divide compounds this picture: Halim and Hidayat (2025) traced a sequential relationship in which device access shapes digital literacy, which in turn shapes technology usage patterns and learning outcomes among Indonesian university students, while Simanjuntak et al. (2025) documented substantial variation in digital literacy across 2,921 Indonesian university students nationwide. Evidence from development country context about bandwidth availability and device access is also captured in India (Muthuprasad et al. 2021).

The Moolang platform evaluated in this study is a browser-based virtual classroom that delivers course material as short case-study text followed by an interactive badge-rewarded quiz (students read a market scenario, respond to structured questions embedded in the platform, receive an immediate score and badge upon completion and enables lecturers to monitor class-wide progress from the lecturer dashboard). Evidence on badge-based gamification specifically is mixed. While students generally report positive attitudes toward badges as a motivational feature, some controlled studies have found badges alone do not reliably translate into higher academic performance without being paired with substantive formative content (Balci et al., 2022).

The case scenarios used across all four phases require students to reason through a price mechanism directly: an overdemand event and an oversupply event are each presented as a scenario in which students must identify the direction of price change and, in doing so, implicitly weigh the opportunity cost of alternative production or purchasing decisions embedded in the scenario. This is a narrower and more disciplinary claim than saying the platform "teaches demand and supply," and it is the basis on which this study, unlike a number of prior virtual-classroom evaluations, treats the content as economics pedagogy rather than subject-agnostic technology use.

Gamified and quiz-based formative assessment specifically has accumulated strong evidence in the years since virtual classrooms became mainstream. Self-determination theory (Ryan & Deci, 2020) holds that intrinsic motivation is supported when a task satisfies needs for competence, autonomy and relatedness; a quiz that gives immediate, specific feedback on a case a student has just reasoned through plausibly supports the competence need in a way a delayed, unmarked written test does not. This mechanism is consistent with more recent outcome evidence. Kaya and Ercag (2023) and Hamari et al. (2016), applying flow theory (Csikszentmihalyi, 1990) alongside self determination theory, found that challenge-based gamification significantly increased academic performance and motivation among distance-learning university students. Campillo Ferrer et al. (2020) found that challenge-based gamification significantly increased academic performance and motivation among distance learning university students. Zainuddin (2023) found that gamification-based quiz instruction produced statistically significant learning gains in a remote Indonesian higher education setting. a pattern consistent with a broader meta-analysis finding a moderate, positive overall effect of gamified interventions on student behavioral outcomes. an effect notably larger among higher-education students than K-12 students (Kim & Castelli, 2021). A meta-analysis by Gyedu et al. (2026) found the overall effect of gamification on learning outcomes was

strongest in Business and quantitative disciplines specifically. In an Indonesian higher-education setting specifically, Zainuddin (2023) found that gamification-based quiz instruction delivered through affordable, easy-to-use platforms significantly increased student engagement and learning outcomes during remote instruction.

The case for treating Moolang's relevance as extending toward entrepreneurship education and not only economic literacy, follows from recent evidence that digital platforms can shape entrepreneurial orientation, though this connection needs to be stated as a plausible extension rather than a measured outcome of the present study. Grivokostopoulou et al. (2019) found that a gamified virtual entrepreneurship environment increased motivation and supported entrepreneurial mentality; Wibowo et al. (2024) found that perceived ease of use and usefulness of digital tools predict digital entrepreneurial self-efficacy among Indonesian students; and Wardoyo et al. (2021) found that entrepreneurial self-efficacy and intention serially mediate the path from digital entrepreneurship education to digital business creation. None of these constructs, entrepreneurial intention, self-efficacy or opportunity recognition, were measured in the present study and none of the instructional design here explicitly taught them; the connection drawn is that the case-based reasoning format shares structural features with interventions in that literature, which is a basis for future research, not a claim this study's data can support on its own.

Despite this growing body of adjacent evidence, no study to date has evaluated a virtual learning platform's effect on economics-specific content mastery under the variable internet-connectivity conditions typical of Indonesian higher education using an analysis appropriate to the platform's own repeated-assessment structure. Prior evaluations in this space have generally either ignored connectivity heterogeneity or analyzed repeated within-subject assessments with statistical methods designed for independent samples. This gap matters practically as well as statistically. Indonesian institutions adopting platforms like Moolang need evidence that holds up under the connectivity conditions they actually have, not only under favorable ones and they need that evidence analyzed in a way that does not overstate certainty the data cannot support. This study addresses not merely an unaddressed topic but methodological inconsistency running through the adjacent literature. Studies that do report repeated within subject assessment generally analyse them with statistical methods designed from independent samples which understates the precision available from a repeated measures design and leaves the trajectory of effect across instructional phases rather than their endpoint unexamined. The present study is positioned to close both gaps at once. The substantive gap (connectivity conditioned effectiveness for economics on specific content) and the analysis matched to the data's repeated phase structure.

This study evaluates the Moolang virtual platform's effect on student learning outcomes in an economics course across four instructional phases, applying a mixed-design ANOVA appropriate to the repeated-phase structure of the data and secondarily discusses implications for entrepreneurship education and for the technological readiness of the economics teachers who would sustain its use. The following hypotheses were tested:

H1: In phase 1, there was a difference in the average learning outcomes of the Moolang class and the control class.

- H2: In phase 2, there was a difference in the average learning outcomes of the Moolang class and the control class.
- H3: In phase 3, there was a difference in the average learning outcomes of the Moolang class and the control class.
- H4: In phase 4, there was a difference in the average learning outcomes of the Moolang class and the control class.
- H5: There is a significant interaction between Group (Moolang Experimental vs Control class) and Phase 1-4 in predicting learning outcomes.

RESEARCH METHOD

The Moolang study uses a quasi-experimental approach with a comparative design (Shadish, Cook & Campbell, 2002) to measure student learning outcomes. The research methodology was designed to assess the impact of virtual learning platforms on student learning outcomes through systematic comparisons between experimental and control groups during four different learning phases.

Participants in this study were students from two national universities in Indonesia: Universitas Negeri Malang (experimental group, n=30) and State University of Surabaya (control group, n=30). These two institutions were selected primarily for accessibility and an existing research collaboration between the author team and contacts at both universities, rather than through a formal sampling frame; this practical basis for selection is discussed further in the Limitation section. No additional inclusion or exclusion criteria beyond enrollment in the relevant economics course were applied and participation was based on oral informed consent obtained from students prior to the first session. All 60 participants completed all four learning phases; there was no attrition.

The two groups are considered comparable on structural grounds. Both Universitas Negeri Malang and State University of Surabaya are Indonesian public universities. Both institutions offer an accredited undergraduate economics education program under the same national higher-education curriculum framework and both cohorts were third-year students of comparable age (concentrated at 19-20 years) enrolled in the same introductory economics course covering demand and supply material. This structural comparability is offered as a partial justification. Students in both cohorts had completed at least one prior semester of coursework and reported no prior exposure to the Moolang platform specifically though general prior exposure to virtual learning platforms during and after the 2020-2021 shift to remote instruction was common to both groups and was not separately measured.

Internet connection quality was based on students' own self-reported assessment of their typical connection at the time of the study (categorized as "strong" or "weak" by student response) rather than a measured bandwidth threshold, with an even distribution obtained between the two categories (50% each). This self-report approach is a measurement limitation acknowledged in the Limitation section, but it was adopted deliberately so that the categorization would reflect students' lived experience of connectivity rather than a momentary technical reading that might not represent their typical access.

Seven virtual learning platforms were evaluated against seven criteria to select a platform for the study: freeware availability, customizability, class-management functionality, not requiring the instructor to build challenges from scratch, support for individual student tracking, an engaging ("fun") user experience and straightforward badge management (Huang & Zhi, 2023). Moolang was selected because it satisfied all

seven criteria, whereas the other six platforms each failed at least one, most commonly requiring instructors to manually construct gamification challenges or lacking individual-level progress tracking; a full platform-by-platform comparison was outside this study's scope but is a reasonable direction for future instrument-development research. The experiment was carried out in four phases described below.

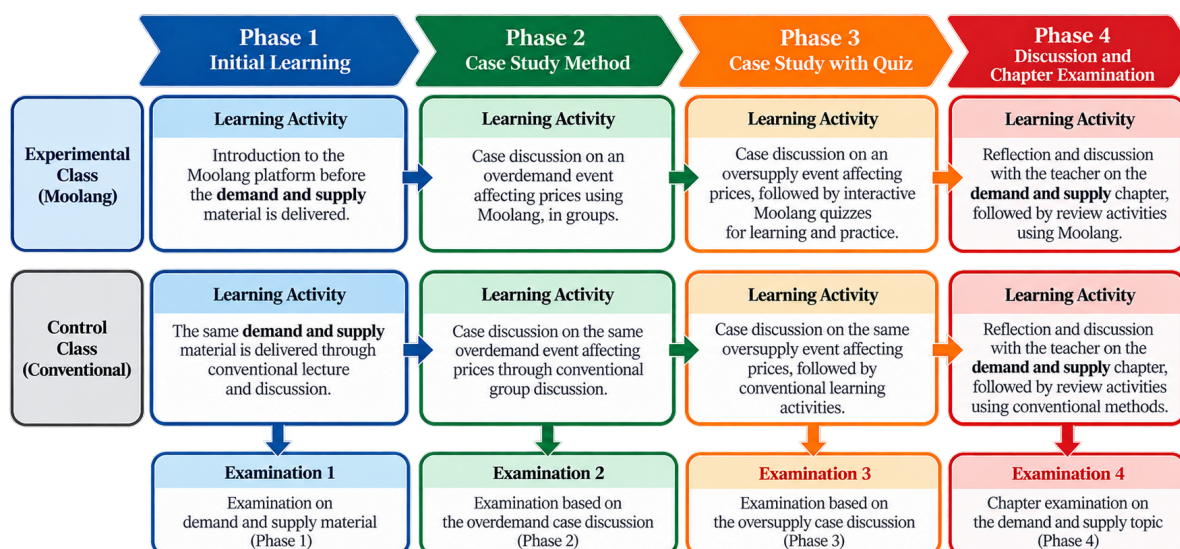


Figure 1. Experiment Flowchart
Source: Developed by Author

Phase 1 (initial learning): the Moolang class received an explanation of the Moolang platform before the demand and supply material was delivered; the control class began the same material through conventional lecture and discussion. Phase 2 (case study method): both classes discussed an overdemand event affecting prices, with evaluation based on the phase 2 case discussion. Phase 3 (case study with quiz): both classes discussed an oversupply event affecting prices, with the experimental class assessed through interactive Moolang quizzes and the control class through conventional paper-based tests. Phase 4 (discussion with teachers and chapter exam): both classes reflected on the demand and supply chapter before completing exam questions, delivered as Moolang quizzes for the experimental class and as exam papers for the control class.

Data collection was carried out through assessment instruments provided at the end of each learning phase. The assessment instrument was designed to measure understanding and application of demand-and-supply concepts and its content validity was evaluated by a panel of subject matter experts. Instrument reliability was determined through Cronbach's alpha with a minimum acceptable value of 0.7.

Prior to the main analysis of this paper phase. Normality was assessed following Kline (2011) and Hair et al. (2019) and Levene's test was used to confirm homogeneity of variance. Because the same 60 students were assessed at all four phases, the primary analysis used a mixed-design (split-plot) ANOVA, with Group (experimental vs. control) as the between-subjects factor and Phase (1-4) as the within-subjects factor, rather than treating the four phases as independent samples. This choice follows methodological guidance that aggregating or treating repeated measurements as independent samples violates the independence assumption underlying standard ANOVA and can bias results, whereas a design that explicitly models the within-subject correlation structure does not (Muhammad, 2023). Mauchly's test was used to check the sphericity assumption

for the within-subjects factor and the Greenhouse-Geisser correction was applied where sphericity was violated. Independent-samples comparisons within each phase (supporting H1-H4) remain valid as reported, because within any single phase the experimental and control groups consist of different individuals.

RESULTS AND DISCUSSION

Results

Participant Characteristic

The data collected is representative of the demographics of respondents. Based on the analysis, the data obtained are presented in Table 1 below.

Table 1. Respondent Characteristics

Characteristic	Category	Frequency	%
Age	20 years old	26	43.3
	19 years old	32	53.3
	18 years old	2	3.3
University	Universitas Negeri Malang (Experiment)	30	50
	State University of Surabaya (Control)	30	50
Gender	Male	17	28.3
	Female	43	71.7
Internet Connection	Strong Connection	30	50
	Weak Connection	30	50
Students Learning Preferences	Virtual Learning	32	53.3
	Classical Learning	28	46.7

Source: Primary data (2026)

The concentration of respondents at age 19 reflects the typical age of third-level students in Indonesian universities. Internet connectivity was balanced by design (50:50) rather than occurring naturally, so that platform performance could be evaluated under both conditions. Students learning preference results, gathered after participants had experienced both virtual and traditional media, showed a near-even split, with a modest lean toward virtual learning (53.3%).

Normality and Homogeneity

Prior to performing differential testing, data normality testing had been performed using an approach developed by Kline (2011) and Hair et al. (2019), which stated that the absolute slope value should be lower than eight or around the absolute value of 1.0 to indicate that the data was normally distributed.

Table 2. Descriptive Statistic by Phase

Phase	Group	N	Mean	Std.Dv	Min.	Max.
Phase 1	Control	30	85.87	5.34	74.00	95.00
Phase 1	Moolang	30	86.73	6.32	70.00	96.00
Phase 2	Control	30	84.00	4.26	75.00	91.00
Phase 2	Moolang	30	86.13	3.46	79.00	95.00
Phase 3	Control	30	82.17	4.15	75.00	90.00
Phase 3	Moolang	30	89.63	3.92	83.00	97.00
Phase 4	Control	30	84.97	4.44	75.00	95.00
Phase 4	Moolang	30	88.40	4.97	75.00	95.00

Source: Primary data, Processed by JASP (2026)

Skewness and kurtosis values across all phases fell within the bound used by Kline (2011) and Hair et al. (2019) to indicate approximate normality, so the data proceeded to homogeneity testing. Levene's test confirmed homogeneous variances across all four learning outcome measures (Phase 1: $F = 1.282$, $p = 0.262$; Phase 2: $F = 3.264$, $p = 0.076$; Phase 3: $F = 0.077$, $p = 0.783$; Phase 4: $F = 0.448$, $p = 0.506$).

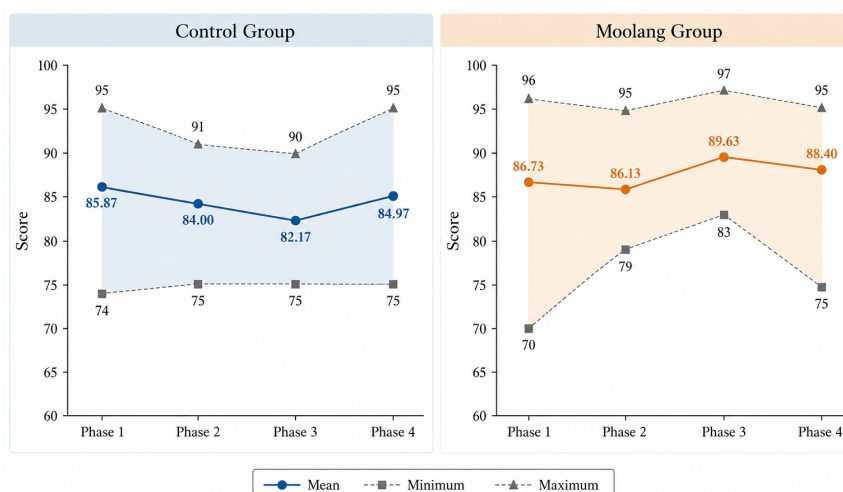


Figure 2. Comparison mean, min, max between classes based on phase
Source: Generated by AI Platform

Figure 2, shows that in phase 1, the control and Moolang class start with the lowest value of the entire phase because it has just started the class with their respective processes. The control class had the highest score in phase 1 with a score of 95, the lowest score of the control class and the Moolang class occurred in phase 1 with a score of 74 and 70. The Moolang class had the highest score in phase 3 with a score of 97 and obtained the lowest score at phase 1. A significant difference occurred in phase 3, where the average grade of the class taught with the virtual class (Moolang class) had an average score of 89.63 while in the said phase, the control class had the lowest average score throughout the 4 learning phases it went through with a score of 82.17.

Hypothesis Testing: Per-Phase Comparisons

Phase 1 testing showed no significant difference between the Moolang and control classes ($p = 0.568$, $d = 0.15$), indicating a comparable baseline before the platform's effect emerged. Phases 2 through 4 each showed a significant and progressively then partially receding advantage for the Moolang class, peaking at Phase 3 with a large effect size ($d = 1.85$, exceeding Cohen's (1998) benchmark for large effect). H1 is rejected; H2, H3 and H4 are accepted (Table 3).

Table 3. Independent- Samples Comparison (Control Vs Moolang) by Phase

Phase	Mean Difference	t	p	Cohen's d
1	0.867	0.574	0.568	0.15
2	2.133	2.129	0.038*	0.55
3	7.467	7.171	< .001**	1.85
4	3.433	2.822	0.007*	0.73

Source: Primary data processed by JASP (2026); Note. (*P-value <.05, **P-value <.001)

Hypothesis Testing (Mixed-Design ANOVA)

Table 4. Mixed-Design (Split Plot) Anova: Group x Phase

Effect	df	F	p	Partial η^2
Group (between-subjects)	1, 58	34.37	<.001	.372
Phase (within-subjects)	3, 174	1.29	.278	.022
Group × Phase (interaction)	3, 174	5.52	.001	.087
Group × Phase (Greenhouse-Geisser corrected)	2.47, 143.38	5.52	.003	.087

Source: Primary data processed by JASP (2026); Note: The Greenhouse-Geisser correction ($\epsilon = .824$) is reported alongside the uncorrected result

The Group main effect was significant and large, confirming that the Moolang class outperformed the control class overall. The Phase main effect alone was not significant, meaning that averaged across both groups, scores did not change significantly from Phase 1 to Phase 4. The Group × Phase interaction was significant both before and after the Greenhouse-Geisser correction, confirming H5: the pattern of change across phases differed between the Moolang and control classes. Read together with Table 3, this indicates the control class remained comparatively flat across phases while the Moolang class widened its advantage through Phase 3 before narrowing slightly at Phase 4, rather than both groups changing at the same rate.

Discussion

The data show that the two groups began from a statistically indifference baseline and that divergences were not a steady or monotonic trend but concentrated at phase 3. The data do not identify specific features of the moolang intervention whether the case study format, immediate feedback quizzes, badge elements or all combinations are responsible for this pattern. All of those components were not identified separately. The data also do not rule out the possibility of contributions from the institutional or instructor level to the main group effect. This pattern is generally consistent with previous empirical findings showing that gamified quiz based formative assessment improves learning performance in distance learning contexts (Kaya & Ercaq, 2023; Zainuddin, 2023). Earlier research of Zainuddin et al. (2020) also reported a systematic review of gamification empirical effects on learning and instruction. Hamari et al. (2016) research also found that engagement and immersion produced by appropriately challenging game based learning. Jaramillo-Mediavilla et al. (2024) umbrella review of gamification research also documents this pattern at general level with substantial variation in how consistently motivation and performance gains appear across studies. Those studies did not analyze a repeated phase structure of the kind used and limits to direct comparison of the effect trajectories. Based on this discussion, gamification is used in the sense established by Sailer & Homner (2020): the use of game design elements, here badges and immediate scoring, within a non-game instructional context. Landers (2014) proposes a broader theoretical model in which game elements shape learning-relevant psychological and behavioral states that, in turn, affect learning outcomes. Koivisto and Hamari's (2019) review of gamification research similarly found that motivational affordances such as points, badges, and immediate feedback are generally, though not universally, associated with positive engagement outcomes. This is consistent with Sailer & Homner (2020) 40 study meta

analysis which found small but significant positive effects of gamification on cognitive, motivational and behavioral learning outcomes.

The significant Group $\times$ Phase interaction, combined with a non-significant Phase main effect, gives a more precise picture than a simple "gradual improvement" narrative would: it is not that scores rose steadily across phases for everyone, but that the two groups diverged, with the Moolang class's advantage concentrated from Phase 2 onward and largest at Phase 3. This pattern is consistent with Vygotsky's (1978) account of learning as socially mediated internalization of tools within a Zone of Proximal Development (Taber, 2020). Phase 1, students were still adapting to an unfamiliar interface, outside their existing zone of comfortable operation, so no difference from conventional instruction would be expected; by Phase 3, students appear to have internalized the platform's tools rather than treating them as a foreign layer between themselves and the economics content.

The concentration of the effect at Phase 3 which paired the case study with an immediate-feedback quiz, is where Cognitive Load Theory (Sweller, 1988) does real explanatory work rather than being merely invoked. This result is consistent with more recent extensions of cognitive load theory to digital and online learning specifically. Which show that interactive feedback-rich digital elements can support learning even while introducing some extraneous load provided the design aligns that load with the intended learning outcome (Skulmowski & Xu, 2022). The case study functions as a form of pre-training. Students work through the oversupply scenario's price-mechanism logic before being tested on it, which should reduce intrinsic load at the point of assessment relative to encountering the concept and the test simultaneously. The quiz itself then functions as low stakes retrieval practice with immediate feedback. This is consistent with Greving et al. (2023) finding that multiple-choice testing improves retention relative to restudying and with Morris et al. (2021) systematic review identifying low-stakes quizzing as one of the more powerful and consistent formative-assessment interventions in higher education, which plausibly reduces extraneous load relative to a single high-stakes written test, where students must also manage uncertainty about format and pacing on top of the content itself. This reading is compatible with the self-determination account introduced earlier (Ryan & Deci, 2020). The specific feedback on a just-completed case supports the need for competence in a way a delayed written score does not. This result is consistent with Greving et al. (2023) finding that multiple-choice testing improves retention relative to restudying and with Morris et al. (2021) systematic review identifying low-stakes quizzing as one of the more powerful and consistent formative assessment interventions in higher education which plausibly reduces extraneous load relative to a single high-stakes written test, where students must also manage uncertainty about format and pacing on top of the content itself. This reading is compatible with the self-determination account introduced earlier (Ryan & Deci, 2020). The specific feedback on a just-completed case supports the need for competence in a way a delayed written score does not. In different situations, that result is consistent with Karaman's (2021) meta-analysis finding that formative assessment produces substantial learning gains, particularly when it involves direct student participation, a finding Wisniewski et al. (2020) meta-analytic update reinforces specific, task-related feedback produces larger gains than general praise or a bare score, which is a plausible motivational channel through which lower extraneous load translates into higher performance rather than merely correlating with it.

This combination is also where the control class's own pattern becomes informative rather than merely a comparison baseline. The control class recorded its lowest mean of

the four phases at Phase 3 ($M = 82.17$) not at Phase 1. A written test administered without the scaffolding of an immediately preceding, interactive case-processing step plausibly imposed a higher extraneous load precisely when the underlying content, an oversupply scenario, was no more or less complex than the overdemand scenario tested in Phase 2. The Moolang class tested on the same underlying content via the case plus quiz format showed no comparable dip. The control group's within-phase dip against the experimental group's stability on matched content is more informative about the mechanism than either group's trend considered alone and is a comparison the original hypothesis set (built around within-group H5 or H6) was not well positioned to surface.

Because the case scenarios required reasoning through price-mechanism logic and implicit opportunity cost trade offs rather than rote demand-supply labeling, the Moolang platform's benefits plausibly extend toward the kind of applied economic reasoning relevant to entrepreneurship education, though this study did not measure entrepreneurial intention, self-efficacy or opportunity recognition directly. The constructs in Ajzen's (1991) theory of planned behavior and Liao et al. (2022) meta analytic synthesis of 89 entrepreneurial intention studies, jointly shape intention and through it behavior. This connection should be read as a plausible extension rather than a finding this dataset can support on its own. Grivokostopoulou et al. (2019) found that a gamified virtual entrepreneurship environment strengthened entrepreneurial motivation and mentality and a cluster of recent Indonesian studies on digital entrepreneurial intention (He et al., 2023; Wibowo et al., 2024; Wardoyo et al., 2021) reinforces the structural plausibility of this link without this study providing direct evidence for it.

Picciano's (2017) claim that alignment between interactivity, learning content and assessment is what makes an online environment succeed also helps explain why the experimental group's performance was not merely high but stable after Phase 1. Martin and Bolliger's (2018) survey of online learners similarly found that students rate timely feedback and instructor engagement among the most important engagement strategies which is consistent with the quiz's immediate-feedback design being a plausible driver of this stability. This existing competence aligns with evidence that Indonesian students in the East Java region generally possess relatively strong functional digital literacy (Daroin & Auliya, 2022), meaning the interface itself was unlikely to be the limiting factor. Sojanah et al. (2021) building on the TPACK construct as originally formulated by Mishra and Koehler (2006), found that Indonesian economics teachers' overall TPACK levels remain low despite adequate technological knowledge. The newest research, inline with Koehler finding, comes from Satiri et al. (2026) and Watcharasresomroeng (2026) who also found that digital competence is the strongest predictor of instructional quality among Indonesia secondary teachers. A gap consistent with Hood and Littlejohn's (2017) finding that educators must actively reconstruct their own knowledge when learning to integrate unfamiliar digital practices, rather than acquiring it automatically through exposure to the tool. Kholifaturrohman and Mulasiwi (2021), Hood and Littlejohn (2017), and Krisnaresanti et al. (2023) all identified specific TPACK components, technological-pedagogical integration and content knowledge respectively as the weakest links among economics educators. This research findings suggest that Moolang's demonstrated effectiveness in this study should not be read as evidence that any economics teacher could replicate these results without deliberate attention to how the platform is integrated pedagogically.

Indonesia's broader digital transformation context is relevant to interpreting the connectivity results specifically. Dhawan (2020) notes that the COVID-19 crisis

accelerated the transition to digital learning while exposing gaps in digital readiness. Halim and Hidayat (2025) and Simanjuntak et al. (2025) document substantial, unevenly distributed digital literacy and access gaps among Indonesian university students. Raes's (2020) systematic review of synchronous hybrid learning adds that the effectiveness of technology-mediated instruction depends heavily on design and context rather than being guaranteed by the technology itself. That research result highlights why connectivity alone cannot fully explain Moolang's sustained advantage. Against that backdrop, Moolang platform sustaining a significant advantage across both self-reported connectivity conditions is a practically meaningful finding, though it should be read alongside the measurement limitation that connectivity here was self-reported rather than independently measured. The near-even split in stated learning preference (53.3% virtual versus 46.7% classical) should also be read cautiously against Norhasanah's (2022) finding that a clear majority of Indonesian students still prefer face-to-face instruction once convenience is weighed against access concerns. Rogers's (2003) diffusion framework, still the reference model for educational technology adoption as recently as Frei-Landau et al. (2022) study of pandemic era mobile learning uptake, in which adoption moves from early adopters toward an early majority, offers one way to read this sample as positioned between those stages rather than as evidence of a wholesale shift in Indonesian learning culture.

The case-based, applied format is consistent with Narmaditya's (2018) finding that problem-based learning improves critical thinking more effectively than teacher-centered instruction, extended to a virtual, gamified format specifically within economics content. Kardoyo et al. (2020) working specifically within an Indonesian economics education program similarly found that problem-based learning strategies improved students' critical and creative thinking skills to conventional lecture instruction, reinforcing that this pattern is not specific to one institution or cohort. Chen et al. (2021) reviewing online and blended entrepreneurship education found that case-based formats were consistently associated with stronger engagement than passive delivery. This is a pattern the framework Hamad et al., (2026), since case-processing is a form of constructive engagement theorized to produce deeper learning than passive reception. Mensah et al. (2024) add that facilitating conditions are strong predictors of sustained e-learning use in entrepreneurship education specifically, which may partly explain why the experimental group's advantage held rather than declining once the platform's novelty wore off after Phase 1.

The moolang and control classes are drawn from two different universities, not only two connectivity conditions. The instructional material itself was held identical between the two classes at every phase, both discussed the same overdemand and oversupply scenarios in the same sequence, so the content taught is not a plausible source of the observed difference. The Group main effect reported above should therefore be read as the effect of Moolang plus any uncontrolled institutional difference, not as an isolated platform effect. The per-phase comparisons in Table 3 and especially the Phase 1 null result, provide some reassurance that the two groups began from a comparable baseline, but this is not a substitute for a measured covariate.

Taken together, four implications follow. First, the data support a shift from lecture-based transmission toward technology-facilitated constructivist-social models, with Moolang mediating learning within students' zone of proximal development rather than simply digitizing a lecture. Second, the concentration of the effect at Phase 3 underscores that pairing case-based material with immediate-feedback formative assessment, rather than either component alone, is the more decisive design choice. Third, the pattern across

phases indicates a need for phased scaffolding in technology rollout, with intensive support concentrated early and gradually withdrawn. Fourth, given documented TPACK weaknesses among Indonesian economics teachers (Sojanah et al., 2021; Kholifaturrohmah & Mulasiwi, 2021; Krisnaresanti et al., 2023), platform adoption should be paired with targeted teacher training rather than assumed to be self-executing.

CONCLUSION

Fundamental Finding: The Moolang virtual platform produced no significant difference from conventional instruction at baseline. A mixed-design ANOVA appropriate to this study's repeated-phase structure showed a significant Group main effect and a significant Group $\times$ Phase interaction, while the Phase main effect alone was not significant. Per-phase comparisons showed no baseline difference at Phase 1 and a significant, large advantage for the Moolang class at Phase 3, the phase pairing case study with quiz. The pattern reflects divergence between groups rather than a uniform upward trend, with the control class's own within-phase dip at Phase 3 providing corroborating evidence for the proposed cognitive-load mechanism. For economic education, these findings indicate that virtual platforms can strengthen mastery of price-mechanism reasoning when paired with case-based, immediate-feedback assessment rather than deployed as a lecture substitute. For entrepreneurship education, the platform's use of authentic market scenarios suggests a plausible, though unmeasured, extension toward applied entrepreneurial reasoning that future research could test directly. For higher education institutions, gradual adoption with concentrated early-phase support is preferable to immediate full deployment. For economics teacher education programs, documented TPACK gaps indicate that platform rollout should be paired with targeted technological-pedagogical training. The following are the result of the hypotheses posed at the beginning. The phase 1 difference between the moolang and control classes is rejected (H1). The differences at phase 2, 3 and 4 (H2, H3, H4) are each accepted. The two-groups trajectories across phases genuinely diverged rather than moving together (H5 Accepted). **Implication:** This study's findings make two contributions. This study demonstrates that evaluating a repeated phase virtual learning intervention reveals concentrated and non monotonic divergence patterns. This refines how the platform's effectiveness is modeled in future economics education research. The finding that moolang platform advantages remain valid under both reported connectivity conditions provides evidence to institutions in Indonesia that case-study based platforms with formative quizzes can support the teaching and teacher training. **Limitation:** The Moolang and control classes are drawn from two different universities selected for accessibility and existing research collaboration rather than random or stratified sampling; while the instructional material was held identical across both classes at every phase, ruling out curriculum content as a source of the observed difference, instructor quality and institutional academic culture were not measured and could not be statistically controlled, since no pre-test or baseline ability score was collected before the intervention. The internet connectivity was categorized by students' own self-report rather than a measured bandwidth threshold, which trades precision for ecological validity and should be considered when interpreting the connectivity-related findings. The participants were recruited through the two participating economics courses with no additional inclusion or exclusion criteria and gave oral rather than written informed consent, consistent with the low-risk educational nature of the intervention but worth noting for readers applying stricter consent standards. The four phases spanned a single course unit on demand and supply, so findings may not extend to other economics topics

or to retention beyond the assessment window used here. The individual-difference variables plausibly relevant to platform effectiveness, including self-regulated learning, digital literacy and entrepreneurial intention, were not measured directly. **Future Research:** Future studies should collect a pre-test or baseline ability measure before the intervention so that ANCOVA can adjust for pre-existing differences between institutions and should consider random assignment within a single institution where feasible to remove the institutional confound entirely. Measuring connectivity directly (e.g., a speed test at the time of the session) rather than by self-report would strengthen the connectivity-related conclusions. Direct measurement of self-regulated learning, digital literacy and entrepreneurial intention, following the frameworks used by Cheng et al. (2025), Arthur et al. (2025) and Wardoyo et al. (2021), would clarify which individual differences moderate platform effectiveness and would allow the entrepreneurship-education connection raised in the Discussion to be tested directly rather than proposed as a plausible extension.

SUGGESTED AI-USE DISCLOSURE STATEMENT

During the preparation of this work, the authors used chatgpt AI to generate Figure 2. The authors reviewed and verified the figure's accuracy against the underlying data and took full responsibility for its content.

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