Journal of Economics, Entrepreneurship, Management Business and Accounting, 2026, 4(5),533-551.
https://doi.org/10.61255/jeemba.v4i5.1780

The Effect of Learning Innovation and Digital Competence on Perceived Learning Outcomes: The Mediating Role of Self-Directed Learning

Fernando Belo*, Murpin Joshua Sembiring Gurky and David Sukardi Kodrat
Doctoral Program in Management Business, Universitas Ciputra Surabaya, Surabaya, 60219, Indonesia

ABSTRACT

Purpose – Indonesian universities expanded digital learning platforms after 2020, yet many undergraduates have not converted access into self-managed study. This study tested seven paths linking learning innovation and digital competence to perceived learning outcomes, directly and via self-directed learning as mediator, grounded in Self-Determination Theory, whose mechanisms were not measured directly.

Design/methodology/approach – A positivist, cross-sectional survey of 312 undergraduates at a private Surabaya university, following an 85-respondent pilot, analyzed with PLS-SEM in SmartPLS 4, supported by Confirmatory Tetrad Analysis, CVPAT, and a full collinearity assessment.

Findings – The measurement model showed strong reliability and validity (Section 6 limitations apply); the structural model explained substantial variance in outcomes. Learning innovation and digital competence were both significantly associated with outcomes directly. Learning innovation was also associated with self-directed learning, which mediated its pathway; digital competence showed no such association, so mediation did not hold. Results are associational; the cross-sectional, single-source design precludes causal claims.

Originality/Value – Learning innovation and digital competence are associated with outcomes through two distinct routes, not one shared mechanism, consistent with, though not a direct test of, Self-Determination Theory. Pedagogical innovation shows a stronger association with student autonomy than digital competence alone, within this single-university sample.

ARTICLE INFO

Keywords:
Learning Innovation, Digital Competence, Self-Directed Learning, Perceived Learning Outcomes, PLS-SEM

Article Information:
Received: 10/06/2026
Revise: 23/07/2026
Accepted: 08/08/2026

ISSN:
2985-3168 (Online)
2985-3222 (Print)

*Corresponding Author at:
Doctoral Program in Management Science, Universitas Ciputra Surabaya, Citraland, Surabaya, 60219, Indonesia.
E-mail address: fernandobelo01@student.ciputra.ac.id (Fernando Belo)

1. Introduction

Indonesian higher education institutions accelerated their adoption of digital learning platforms after the disruption of 2020. Learning management systems, recorded lectures, and mobile assessment tools now sit inside nearly every undergraduate course. Lecturers report a different problem: students log into these platforms without ever completing a module on their own initiative. Access to digital tools has grown faster than students' capacity to direct their own learning. This gap between digital availability and independent study behavior sits at the center of an unresolved question about how universities should build perceived learning outcomes in a technology-saturated classroom.

Two research streams address this question from different angles. One treats learning innovation, including problem-based learning, flipped classrooms, and interactive teaching, as a direct driver of student outcomes. Bhuttah, Xusheng, Abid, and Sharma (2024) surveyed 321 students across public and private universities in Pakistan and found that innovative pedagogical approaches significantly predicted student learning outcomes ($\beta = 0.551$, $p < 0.001$). A second stream frames digital competence, the systematic integration of digital tools into teaching and administration, as the primary lever for academic quality. Self-Determination Theory (Deci & Ryan, 2000) connects both streams: learning innovation and digital competence raise perceived learning outcomes only when they satisfy a learner's need for autonomy, and self-directed learning is the behavioral expression of that satisfied need.

Rashid and Asghar (2016) tested the direct link between undergraduates' technology use and their academic performance among 761 students and found no significant relationship between the two; academic performance improved only indirectly, through self-directed learning and student engagement. This null-direct-path, working-mediator pattern raises a real possibility for the present study: learning innovation and digital competence may show a similarly weak or non-existent direct effect on perceived learning outcomes, and self-directed learning may be the mechanism that has been doing the actual work in prior models without being tested as an explicit mediator.

This study tested whether learning innovation and digital competence are associated with perceived learning outcomes directly and indirectly through self-directed learning. It specified seven hypothesized paths and analyzed them with Partial Least Squares Structural Equation Modeling, a method suited to multi-construct models with an explicit mediator and no requirement of normally distributed data. The sample was undergraduate students at a private university in Surabaya, Indonesia, an institution that has run both curriculum-level pedagogical innovation and a campus-wide digital transformation initiative within the past three academic years, making it a relevant setting to isolate the mediating mechanism; the initiative describes the institutional context in which respondents were recruited and is distinct from the individual-level digital competence construct this study measures.

Because this study measures self-directed learning as an outcome rather than measuring autonomy need satisfaction, competence, or relatedness directly, a supported mediating role for self-directed learning would be consistent with, rather than a direct test of, Self-Determination Theory in a digitally mediated higher education context; that distinction is carried through the interpretation in Sections 2 and 5. The next section develops the theoretical model and states the seven hypotheses that structure the analysis.

2. Literature Review & Hypothesis Development

2.1 Self-Determination Theory as the Grounding Framework

Self-Determination Theory holds that motivation and behavior change become self-sustained when an environment satisfies three basic psychological needs: autonomy, competence, and relatedness (Deci & Ryan, 2000). Applied to higher education, a course design or a digital platform functions as autonomy-supportive when it gives students real choice over pace, method, and depth of study. Self-directed learning is the behavioral signature of a satisfied autonomy need: the learner sets goals, selects resources, and evaluates progress without waiting for external instruction. This study treated learning innovation and digital competence as two distinct candidate autonomy-supportive conditions and tested whether each was associated with perceived learning outcomes by first strengthening self-directed learning, while treating the autonomy-support label itself as a proposition rather than a directly measured property, consistent with the caveat discussed further in Section 4.This positioning needs an important qualification for digital competence specifically. Self-Determination Theory's autonomy-support construct describes a property of the social or instructional environment, a course design, a teacher's communication style, a platform's choice architecture, not a property of the individual using that environment. Digital competence, as operationalized here, is an individual capability: a student's own skill in navigating digital tools. A student can be highly digitally competent without the surrounding environment giving that student any more choice over pace, method, or depth of study, so a significant digital-competence effect does not, on its own, indicate that autonomy support was present or that an autonomy need was satisfied. Learning innovation maps onto the environmental side of the theory more directly, since problem-based and flipped formats are properties of how instruction is designed, but even that mapping is inferred from instructional design features rather than from a direct measure of felt autonomy. Because autonomy, competence, and relatedness were not measured, Self-Determination Theory is used here as an interpretive lens for organizing the hypotheses and discussing the pattern of results, not as a causal mechanism the data directly test; Section 4 returns to this distinction when interpreting the two antecedents' structurally different paths. Frameworks that speak more directly to the constructs actually measured, including self-regulated learning models of goal-setting and monitoring, social cognitive theory's account of self-efficacy and modeled behavior, or technology-acceptance and technology-supported learning perspectives, offer alternative explanations for the same pattern of paths and are not ruled out by this design.

2.2 Learning Innovation and Perceived Learning Outcomes

Learning innovation, understood as the deliberate redesign of instruction through problem-based learning, flipped classrooms, and interactive teaching, is theorized to raise perceived learning outcomes by increasing the cognitive demand placed on learners. Bhuttah et al. (2024) tested this link directly among Pakistani university students and found that innovative pedagogical approaches positively and significantly predicted student learning outcomes, alongside a significant effect on critical thinking. The same study found inclusive leadership strengthened, rather than replaced, this direct path, indicating the innovation-to-outcome link holds even after accounting for institutional support. No study reviewed for this proposal reported a null or negative direct effect of learning innovation on student-level outcomes, which strengthens rather than weakens the case for testing the path in an Indonesian setting where the construct remains underexamined.

H1: Learning innovation has a significant positive effect on perceived learning outcomes.

2.4 Digital Competence and Perceived Learning Outcomes

Digital competence is theorized to raise perceived learning outcomes by expanding access to personalized, on-demand instructional content. Song, Lv, Wang, Wang, and Dong (2025) tested this link among Chinese undergraduates and found digital learning competence significantly and positively predicted academic achievement. Zakir et al. (2025) reported a parallel result: digital literacy improved academic performance directly and through digital informal learning, self-efficacy, and digital competence as mediators. Sun and Yoon (2025) extended a related pattern to faculty, finding institutional digital transformation, a construct distinct from the individual digital competence measured in the present study, significantly predicted faculty performance, though that result speaks to instructors rather than students directly. Gutu, Medeleanu, and Asiminei (2024) complicate this picture: among a large sample of European students, higher education digitalization reduced learning engagement rather than raising it. This tension between a construct that helps academic achievement in one study and hurts engagement in another motivates testing digital competence's effect through self-directed learning rather than assuming a single uniform direct effect.

H2: Digital competence has a significant positive effect on perceived learning outcomes.

2.5 Learning Innovation and Self-Directed Learning

Learning innovation is theorized to build self-directed learning by shifting instructional control from the lecturer to the student, a mechanism Self-Determination Theory frames as autonomy support (Deci & Ryan, 2000). Bhuttah et al. (2024) found that innovative pedagogical approaches significantly raised student critical thinking, a cognitive precursor to independent goal-setting and self-monitoring. Direct empirical tests of the specific path from learning innovation to self-directed learning remain scarce in the reviewed literature, which itself signals an underexamined mechanism rather than a settled null finding. This study treats the theoretical argument, supported by adjacent evidence on critical thinking and engagement, as sufficient grounds for a directional hypothesis, while flagging the path as one of the study's more exploratory contributions.

H3: Learning innovation has a significant positive effect on self-directed learning.

2.6 Digital Competence and Self-Directed Learning

Digital competence is theorized to build self-directed learning by giving students tools to set their own pace and revisit content independently. Rashid and Asghar (2016) tested this link directly among undergraduate students and found technology use significantly and positively predicted self-directed learning, alongside a significant effect on student engagement. Lee and Chang (2025), synthesizing a body of studies in a meta-analysis of digital learning environments, confirmed that digital learning conditions support measurable self-directed learning competencies, though their sample centered on K-12 contexts and the finding should transfer to higher education with some caution. Together, the two sources support a direct positive path from digital competence to self-directed learning in the proposed model.

H4: Digital competence has a significant positive effect on self-directed learning.

2.7 Self-Directed Learning and Perceived Learning Outcomes

Self-directed learning is theorized to raise perceived learning outcomes because learners who set their own goals and monitor their own progress engage more deeply with course material than learners who wait for external direction. Lee and Chang (2025) found in their meta-analysis that self-directed learning significantly improved learning performance compared with traditional teaching. Rashid and Asghar (2016) reported a compatible mechanism: academic performance was affected by technology use only indirectly, through self-directed learning and engagement, not through a direct path, which positions self-directed learning as the operative link rather than a background variable. Both sources converge on the same direction and support specifying self-directed learning as the structural model's central mediator.

H5: Self-directed learning has a significant positive effect on perceived learning outcomes.

2.8 The Mediating Role of Self-Directed Learning

Self-directed learning is proposed as the mechanism that explains how learning innovation and digital competence reach perceived learning outcomes, not as a parallel predictor sitting beside two already-sufficient direct paths. Rashid and Asghar (2016) reported this exact pattern for technology use, which reached academic performance only through self-directed learning and student engagement, without a significant direct path of its own. This precedent justifies treating self-directed learning as a genuine mediator in this model rather than assuming its role from the four direct and antecedent-level hypotheses alone, and motivates stating the indirect effects as their own testable hypotheses. A second precedent for this pattern, Shafait, Khan, Bilan, and Oláh (2021), was cited in earlier versions of this argument but has since been removed: the article was retracted by PLOS ONE in October 2025 following the editors' concerns about manipulation of the peer review process, and its findings are not relied upon anywhere in this manuscript. The theoretical motivation for treating self-directed learning as a mediator therefore rests on the Rashid and Asghar (2016) precedent alone, which is a narrower evidentiary base than the two-study convergence claimed in an earlier version of this manuscript.The precedent above establishes full mediation, no significant direct path once the mediator entered the model, not because a direct channel is theoretically implausible but because that specific sample found no evidence for one. This study does not assume that same outcome in advance. H1 and H2 test whether learning innovation and digital competence retain a significant direct association with perceived learning outcomes alongside the mediation hypothesized in H6 and H7, so the design can return full mediation, complementary partial mediation, or a direct-only pattern for either antecedent, and does not presuppose which of the three applies before estimation. Testing direct and indirect paths together is therefore part of the original design rather than a change introduced after seeing the results; the precedent motivates expecting self-directed learning to carry real explanatory weight for at least one antecedent, not expecting it to fully displace both direct paths.

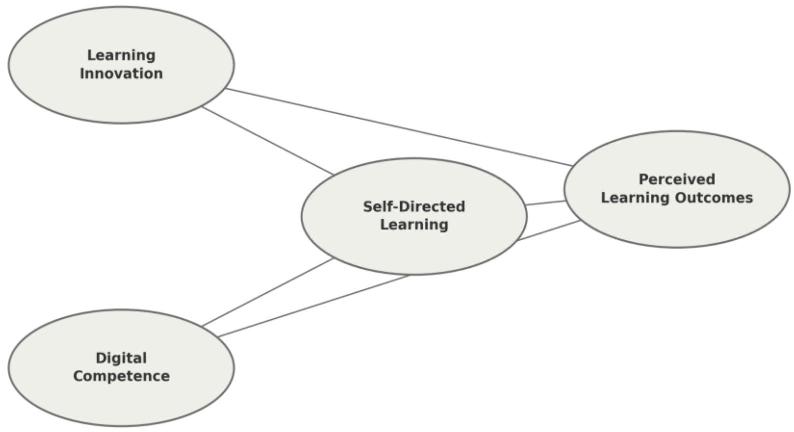
H6: Self-directed learning mediates the effect of learning innovation on perceived learning outcomes.

H7: Self-directed learning mediates the effect of digital competence on perceived learning outcomes.

2.9 Conceptual Model

The structural model specifies seven hypotheses: two direct paths from learning innovation and digital competence to perceived learning outcomes (H1, H2), two paths from learning innovation and digital competence to self-directed learning (H3, H4), one path from self-directed learning to perceived learning outcomes (H5), and two specific indirect effects positioned as standalone mediation hypotheses, learning innovation to perceived learning outcomes through self-directed learning (H6) and digital competence to perceived learning outcomes through self-directed learning (H7). All seven paths were tested in SmartPLS 4 using the final sample described in Section 3.

Figure 1. Proposed conceptual model of the study



Source: Authors' own construction (2026).

3. Methodology

3.1 Research Paradigm, Design, and Sampling

This study adopts a positivist paradigm and a quantitative, cross-sectional survey design, consistent with the hypothesis-testing objective stated above. Partial Least Squares Structural Equation Modeling (PLS-SEM) is the analysis technique used. The model tests a mediation mechanism with a moderate sample of 312 respondents, and PLS-SEM does not require multivariate normal data, a common condition in Likert-scale survey research (Hair, Risher, Sarstedt, & Ringle, 2019). None of these reasons alone establishes that PLS-SEM is preferable to covariance-based SEM for this specific model: a four-construct, seven-hypothesis mediation structure with 312 respondents is not unusually complex, and covariance-based SEM can estimate a comparable mediation model under non-normal data using robust maximum-likelihood estimators or bootstrapped standard errors. PLS-SEM is used here because it is the established convention in this study's closest comparison studies (Bhuttah et al., 2024; Song et al., 2025; Rashid & Asghar, 2016) and because the predictive-assessment components reported in Section 4, CVPAT and PLSpredict, are native to the PLS-SEM framework; covariance-based SEM remains a viable, and arguably underused, robustness alternative for future replications of this model, particularly if the research question shifts from prediction toward strict confirmatory theory testing. The unit of analysis is the individual undergraduate student, not the class, study program, or institution, because all four constructs, learning innovation, digital competence, self-directed learning, and perceived learning outcomes, are measured as individual-level perceptions and behaviors; the unit of observation must match the unit of analysis to avoid an ecological fallacy in the structural model.

Consistent with the individual-level unit of analysis established above, this study applies purposive sampling, restricted to undergraduate students at a private university in Surabaya, Indonesia who have completed at least two semesters and used the institution's digital learning platform, combined with snowball sampling to reach additional eligible respondents through peer referral. The final sample consists of 312 undergraduate students, a figure that exceeds the minimum implied by the ten-times rule for the most complex path in the model, roughly 30 to 50 cases, and satisfies the inverse square root method for minimum sample size in PLS-SEM (Kock & Hadaya, 2018), which recommends a larger sample to detect a path coefficient as small as 0.20 at 80 percent statistical power and a 5 percent significance level. A sample of 312 also matches, coincidentally, the exact scale used by Song et al. (2025) and remains well within the range of Rashid and Asghar (2016) with 761 respondents, supporting the comparability of this study's statistical power to its anchor studies. These sample-size comparisons speak only to statistical power, not to the independence of observations. Response rate, study program, semester, age, gender, academic standing, mode of study, and the specific lecturers or courses respondents were drawn from were not recorded, so this study cannot rule out non-response or self-selection bias, and cannot test directly whether students sharing a lecturer or course produced correlated responses. Because purposive and snowball recruitment at a single institution plausibly draws multiple respondents from the same courses, the 312 observations are treated as a sample whose independence could not be verified rather than as confirmed independent evidence; Section 6 discusses the consequences of this for the standard errors reported in Section 4.

3.2 Instrument

All constructs were measured with a seven-point Likert scale, from 1 (strongly disagree) to 7 (strongly agree), consistent with this research program's established instrument format. Learning innovation items were adapted from the innovative pedagogical approaches scale validated by Bhuttah et al. (2024). Digital competence items were adapted from the digital learning competence scale validated by Song et al. (2025). Self-directed learning items were adapted from the Self-Rating Scale of Self-Directed Learning validated by Fisher, King, and Tague (2001), the same instrument applied by Rashid and Asghar (2016). Perceived learning outcomes items were adapted from the student learning outcomes scale validated by Bhuttah et al. (2024). The questionnaire was prepared bilingually in Bahasa Indonesia and English, translated and independently back-translated by two bilingual experts, with discrepancies reconciled before a pilot test confirmed content and face validity. The pilot test was administered to 85 respondents, drawn from the same population but excluded from the final sample of 312, to check item clarity, sampling adequacy, and completion time before full-scale data collection; construct-level reliability and validity are reported from the final sample in Table 1 (Section 4) rather than duplicated at the pilot stage.

3.3 Common Method Bias

Because all constructs are self-reported by the same respondent in a single-source survey, this study applied both procedural and statistical remedies for common method bias. Procedurally, the questionnaire separates predictor and outcome item blocks, guarantees respondent anonymity, and states explicitly that there are no right or wrong answers. Statistically, this study used Harman's single-factor test as a baseline check, with a decision criterion that the first unrotated factor should explain less than 50 percent of total variance, and an inner-model VIF check in SmartPLS 4 against the 3.3 threshold (Kock & Lynn, 2012); both checks are reported in Section 4, including the exceedance discussed in Section 4 and the scope limitation discussed in Section 6.

3.4 Analysis Technique

The measurement model was assessed for convergent validity through outer loadings, Average Variance Extracted, and Composite Reliability, and for discriminant validity through the Heterotrait-Monotrait ratio, following Hair et al. (2019). Before any path was interpreted, Confirmatory Tetrad Analysis (CTA-PLS) was run on every multi-item construct to check whether its specified measurement mode, reflective rather than formative, was consistent with

the data rather than assumed from theory alone (Gudergan, Ringle, Wende, & Will, 2008), subject to the reporting limitations noted in Section 4.
The structural model was then assessed through path coefficients and bootstrapped significance testing in SmartPLS 4, covering the direct paths (H1 through H5) and the specific indirect effects (H6, H7) that establish the mediating role of self-directed learning. Because significant paths do not by themselves establish predictive quality, this study also used the Cross-Validated Predictive Ability Test (CVPAT) to compare the model against a naive indicator-average benchmark, intended to provide stronger evidence of predictive validity than in-sample R^2 or Q^2predict alone (Liengaard et al., 2021); the planned comparison against an alternative lower-order composite model was not completed, as noted in Section 4. Importance-Performance Map Analysis (IPMA) was considered during the design of this study as a way to translate total effects into intervention priorities (Ringle & Sarstedt, 2016), but it was not executed and is not reported as part of this analysis; Section 4 and Section 6 return to this as an explicit direction for future work rather than a completed technique.

4. Result and Discussion
4.1 Result
4.1.1 Pilot Test
The pilot test (n = 85) confirmed sampling adequacy for factor analysis: the Kaiser-Meyer-Olkin measure was .924, and Bartlett's test of sphericity was significant, $\chi^2(378) = 2779.39$, $p < .001$. An unrotated principal component analysis extracted four components with eigenvalues above 1, together explaining 82.4% of total variance; the first unrotated component explained 53.9% of variance. This figure exceeds the 50% threshold this study itself uses for Harman's single-factor test, and that exceedance is acknowledged directly rather than explained away: by the single-factor criterion alone, common method bias cannot be ruled out in the pilot instrument. The varimax-rotated component matrix is more reassuring, showing every item loading at .73 or above on its own construct with no problematic cross-loading on another component, which suggests the variance is not concentrated in a single latent factor once rotation is allowed; but a rotated pattern and a single-factor variance test answer different questions, and the latter's borderline result is treated here as an unresolved limitation rather than a passed check (see Section 6, Limitations). All communalities exceeded .50 (range .743 to .889), supporting adequate item extraction across all 28 pilot items.
4.1.2 Measurement Model Evaluation
The final sample (n = 312) was used to estimate the measurement model in SmartPLS 4. The self-directed learning construct retained six of its originally proposed seven items; SDL7 was removed during model estimation. This deletion is flagged here rather than only in Section 6: no pre-registered deletion criterion was set before estimation, and SDL7's original loading, item wording, and cross-loading pattern are not reported in this version of the manuscript, which limits an independent reader's ability to judge whether the deletion narrowed the construct's conceptual coverage or simply removed a psychometrically weak item. A sensitivity comparison of the structural results with and without SDL7 has not been run and is listed as a required step before this measurement decision is treated as final. Table 1 reports outer loadings alongside construct reliability and convergent validity. All indicator loadings exceeded the .70 threshold, Cronbach's alpha and composite reliability exceeded .90 for every construct, and Average Variance Extracted (AVE) exceeded the .50 threshold for every construct, jointly supporting convergent validity (Hair et al., 2019).

Table 1. Outer Loadings, Reliability, and Convergent Validity

Construct	Indicator	Loading	Alpha	CR (rho_a)	CR (rho_c)	AVE
Digital Competence	DT1	0.850	0.933	0.935	0.945	0.712
	DT2	0.855				
	DT3	0.839				
	DT4	0.869				
	DT5	0.832				
	DT6	0.816				
	DT7	0.844				
Learning Innovation	LI1	0.867	0.934	0.938	0.946	0.716
	LI2	0.864				
	LI3	0.860				
	LI4	0.852				
	LI5	0.837				
	LI6	0.776				
	LI7	0.865				
Self-Directed Learning	SDL1	0.871	0.922	0.922	0.939	0.719
	SDL2	0.854				
	SDL3	0.857				
	SDL4	0.846				
	SDL5	0.842				
	SDL6	0.815				
Perceived Learning Outcomes	SQ1	0.865	0.922	0.923	0.937	0.681
	SQ2	0.823				
	SQ3	0.851				
	SQ4	0.824				
	SQ5	0.826				
	SQ6	0.824				
	SQ7	0.760				

Discriminant validity was assessed with the Heterotrait-Monotrait ratio (HTMT). All values remained below the conservative .85 threshold (Table 2), supporting discriminant validity among all four constructs.

Table 2. Discriminant Validity (HTMT)

Construct pair	HTMT
Learning Innovation - Digital Competence	0.394
Self-Directed Learning - Digital Competence	0.205
Self-Directed Learning - Learning Innovation	0.563

Perceived Learning Outcomes - Digital Competence	0.469
Perceived Learning Outcomes - Learning Innovation	0.597
Perceived Learning Outcomes - Self-Directed Learning	0.651

Source: SmartPLS 4 output, authors' primary data (2026).

Confirmatory Tetrad Analysis (CTA-PLS, 10,000 bootstrap samples, two-tailed, $\alpha = .10$) tested whether each construct's reflective specification was consistent with the data, using the non-redundant tetrads SmartPLS 4 sampled for each construct (roughly a dozen per construct rather than the complete set, without a multiplicity adjustment). For digital competence, none of the sampled tetrads differed significantly from zero (largest $|t| = 0.85$), supporting a reflective specification. For learning innovation, self-directed learning, and perceived learning outcomes, one sampled tetrad per construct exceeded the critical value (largest $|t| = 2.50$, 1.77, and 2.38, respectively), while the rest were non-significant. This study's decision rule, retaining a reflective specification when only a small minority of sampled tetrads are significant, is a pragmatic threshold rather than a formally derived one; a stricter, multiplicity-adjusted test on the complete tetrad set could reach a different conclusion for these three constructs, carried forward as a limitation rather than resolved here. This decision does not rest on the tetrad test alone. Learning innovation's seven items were adapted as a single set describing one integrated instructional redesign rather than separate sub-scales for problem-based learning, flipped classrooms, and interactive teaching, giving some support to treating them as reflective, though they were not designed to be strictly interchangeable across those elements. Perceived learning outcomes is a harder case: its items span self-reported gains in knowledge, skill, and confidence, facets that could move independently, so a formative or composite alternative remains a live possibility the tetrad evidence alone does not rule out. Re-estimating the model under a formative specification for this construct, compared against Table 3, has not been done and is a required robustness check before the reflective specification is treated as settled.

Two further checks addressed common method bias. First, the inner-model VIFs already reported ranged from 1.16 to 1.54, well below the 3.3 threshold Kock and Lynn (2012) recommend; this tests collinearity along the model's specified paths only, not the full-collinearity test regressing every latent variable on every other regardless of hypothesized structure. That broader regression was not run separately, so the inner-VIF result is partial, structural-path evidence rather than a complete full-collinearity test. Second, because all constructs were measured from the same respondent at the same time with no temporal, source, or instrument separation, these remedies cannot rule out common method bias or reverse causation as fully as a multi-source or multi-wave design would; this limitation carries into every path coefficient in this section and is discussed further in Section 6. Stated directly: students who evaluate their learning experience favorably overall may have rated every construct somewhat more positively together, inflating the magnitude, though not necessarily the sign, of the significant paths for H1, H2, H3, H5, and H6. Table 3 and Table 4's coefficients should be read as an upper-bound estimate of these associations' true strength rather than a bias-free measurement.

4.1.3 Structural Model Evaluation and Hypothesis Testing

The structural model explained a moderate share of variance in self-directed learning ($R^2 = .277$) and a substantial share of variance in perceived learning outcomes ($R^2 = .504$). The Standardized Root Mean Square Residual (SRMR) was .046, below the conventional .08

threshold, and the Normed Fit Index (NFI) was .928; these descriptive indices, adapted from covariance-based SEM, are reported for context but are not treated here as definitive proof of model fit in a variance-based PLS-SEM model, consistent with ongoing debate in the methodological literature about their interpretation outside covariance-based SEM.

Table 3. Path Coefficients and Hypothesis Testing

	H	β	t	p	Decision
Learning Innovation → Perceived Learning Outcomes	H1	0.233	4.389	< .001	Supported
Digital Competence → Perceived Learning Outcomes	H2	0.267	6.381	< .001	Supported
Learning Innovation → Self-Directed Learning	H3	0.526	11.809	< .001	Supported
Digital Competence → Self-Directed Learning	H4	-0.001	0.017	.986	Not supported
Self-Directed Learning → Perceived Learning Outcomes	H5	0.428	8.967	< .001	Supported

Source: SmartPLS 4 bootstrapping output, authors' primary data (2026). Associational language is used throughout; the cross-sectional, single-source design does not support causal interpretation (see Section 6, Limitations).

Table 3 reports the bootstrapped path coefficients (5,000 subsamples) for the five direct hypotheses. Four of the five direct paths were statistically significant.

Table 4. Specific Indirect Effects

Path	H	β	t	p	Decision
Learning Innovation → SDL → Perceived Learning Outcomes	H6	0.225	7.169	< .001	Supported
Digital Competence → SDL → Perceived Learning Outcomes	H7	0.000	0.017	.986	Not supported

Source: SmartPLS 4 bootstrapping output, authors' primary data (2026).

Table 4 reports the two specific indirect effects that test the mediating role of self-directed learning.

Table 5. Direct, Indirect, and Total Effects (Mediation Classification following Zhao, Lynch, & Chen, 2010)

Antecedent → Outcome	Direct effect (H, β, t)	Indirect effect via SDL (H, β, t)	Total effect (β)	Classification
Learning Innovation → Perceived Learning Outcomes	H1: .233 (t=4.389)	H6: .225 (t=7.169)	.458	Complementary partial mediation
Digital Competence → Perceived Learning Outcomes	H2: .267 (t=6.381)	H7: .000 (t=0.017, ns)	.267	Direct-only (no mediation)

Table 5 consolidates the direct, indirect, and total effects reported separately in Table 3 and Table 4, following Zhao, Lynch, and Chen's (2010) mediation typology rather than variance-accounted-for language. For learning innovation, both the direct effect (H1) and the indirect effect through self-directed learning (H6) are significant and share the same sign, which Zhao et al. (2010) classify as complementary partial mediation: self-directed learning explains part, not all, of learning innovation's association with perceived learning outcomes. For digital competence, the direct effect (H2) is significant but the indirect effect (H7) is not distinguishable from zero, so the association is direct-only; self-directed learning is not a mediating mechanism for this antecedent in the present sample. Presenting the two antecedents side by side this way is intended to document the complementary partial mediation classification for H6 formally rather than leaving it to be inferred from the discussion alone.

Effect sizes (f^2) followed the same pattern: learning innovation had a large effect on self-directed learning ($f^2 = .330$) and a small effect on perceived learning outcomes ($f^2 = .071$); self-directed learning had a medium effect on perceived learning outcomes ($f^2 = .267$); digital competence had a small-to-medium effect on perceived learning outcomes ($f^2 = .124$) but a negligible effect on self-directed learning ($f^2 < .001$), mirroring the non-significant H4 path.

4.1.4 Predictive Relevance

PLSpredict Q^2predict values were positive for both endogenous constructs (self-directed learning = .265; perceived learning outcomes = .361), indicating the model outperforms a naive mean-based benchmark within this sample. These are construct-level Q^2predict values; indicator-level PLSpredict RMSE and MAE, benchmarked against a linear-model comparison for each item, were not computed for this study and are listed as a required addition alongside the missing alternative CVPAT benchmark noted below. The Cross-Validated Predictive Ability Test (CVPAT) compared the model against an indicator-average benchmark across a 10-fold cross-validation within the same 312-respondent sample. The model produced significantly lower prediction loss than the naive benchmark for both self-directed learning ($t = 4.971$, $p < .001$) and perceived learning outcomes ($t = 6.006$, $p < .001$), and overall ($t = 6.515$, $p < .001$). The methodology in Section 3 also proposed comparing the model against an alternative lower-order composite benchmark; only the indicator-average comparison is reported here because that second benchmark was not run, and this omission is noted rather than implied as complete. These results should be read narrowly: CVPAT and Q^2predict demonstrate that the model predicts held-out observations better than a naive benchmark under internal cross-validation within this sample. They are evidence of internal predictive validity, not of external generalizability to other universities, cohorts, or national contexts, and the discussion and conclusion do not extend these results beyond that internal claim. Importance-Performance Map Analysis (IPMA) was proposed in Section 3 as part of the analytical design, but no IPMA output was produced for this study; because a proposed method with no reported results should not remain part of the analytical design or practical logic, IPMA is treated here as future work, not as a completed analysis, and is not invoked to justify any intervention priority in Section 5.

4.2 Discussion

Learning innovation was significantly and positively associated with perceived learning outcomes, consistent with the hypothesized direct path. This result corroborates Bhuttah et al. (2024), who found innovative pedagogical approaches significantly predicted student learning outcomes among Pakistani university students, and extends that finding to an Indonesian private-university setting that the literature review in Section 1 identified as underexamined.Finding the same direction in a second, non-probability sample from a different national setting is a modest form of replication, but it rests on two cross-sectional, single-country studies using different instruments and populations; that is a narrower basis than is needed to call learning innovation a generalizable driver, and the claim here is limited to noting the direction replicates rather than to asserting external validity beyond these two samples.

Digital competence was also significantly and positively associated with perceived learning outcomes directly, a direction consistent with Song et al. (2025) and Zakir et al. (2025), both of which found digital-related constructs significantly predicted academic performance among Asian university students. That comparison should be read as directional rather than as evidence the two outcomes are interchangeable: Song et al. (2025) and Zakir et al. (2025) measured academic achievement through performance-based indicators, while perceived learning outcomes here is self-reported, so the present result and those two studies converge on the sign of the relationship, not on a shared operationalization of the dependent variable. This convergence across three studies conducted in different national contexts strengthens confidence that digital competence is associated with a positive learning-related outcome through some direct channel, even though, as Section 4 discusses, that channel does not appear to run through self-directed learning in the present sample.

Learning innovation was the strongest predictor of self-directed learning in the entire model, supporting the Self-Determination Theory argument developed in Section 2 that autonomy-supportive instructional redesign, rather than mere content delivery, is what builds a learner's capacity for self-management. This finding is consistent with the theoretical link Bhuttah et al. (2024) drew between innovative pedagogy and the cognitive precursors of independent learning, and it strengthens the case, flagged in Section 2 as exploratory, that learning innovation is a genuine antecedent of self-directed learning rather than only of perceived learning outcomes directly.

Contrary to the hypothesized positive relationship, digital competence showed no meaningful relationship with self-directed learning. This null finding is not an isolated anomaly; it echoes the tension identified in the Introduction between Gutu et al. (2024), who found higher education digitalization reduced students' learning engagement rather than strengthening it, and studies reporting positive digital effects on more distal outcomes. It is also consistent with the broader empirical literature reviewed by Bulman and Fairlie (2016) in the Handbook of the Economics of Education, which concluded that access to educational technology does not automatically translate into improved learning behavior or outcomes, and that its effects depend heavily on how the technology is actually used rather than on its mere availability. Where Rashid and Asghar (2016) found a significant positive link between technology use and self-directed learning among undergraduates in a different national setting, the present sample of Indonesian undergraduates showed no such link. Read together with the digital-divide literature on Indonesian higher education, which documents uneven infrastructure quality, instructor readiness, and student digital competence across institutions, this suggests the digital-competence-to-self-direction pathway is more culturally and institutionally contingent than the originally hypothesized universal mechanism, and should not be assumed to hold outside the specific technological and pedagogical conditions under which it was previously observed.

Self-directed learning was significantly and positively associated with perceived learning outcomes, the second-strongest path in the model after learning innovation's effect on self-directed learning itself. This result is consistent with the meta-analytic evidence in Lee and Chang (2025), who synthesized findings across multiple digital learning environments and found self-directed learning reliably improved learning performance relative to traditional instruction. The size of this path relative to the two direct paths (H1, H2) indicates self-directed learning is not merely a plausible mediator but a substantively important one for perceived learning outcomes in its own right.

Self-directed learning significantly mediated the relationship between learning innovation and perceived learning outcomes. Because the direct path from learning innovation to perceived learning outcomes (H1) was also significant, this pattern is consistent with complementary partial mediation: learning innovation is associated with perceived learning outcomes both directly and indirectly, by first strengthening students' capacity for self-directed learning. This dual pathway supports the theoretical argument in Section 2 that self-directed learning is a genuine mechanism for the learning-innovation pathway specifically, not an interchangeable stand-in for any antecedent in the model.

Self-directed learning did not mediate the relationship between digital competence and perceived learning outcomes, a direct consequence of the null H4 path: a construct cannot transmit an effect it does not itself receive. This non-finding is theoretically informative rather than merely a statistical footnote. It indicates that digital competence's significant direct effect on perceived learning outcomes (H2) operates through a mechanism this model did not measure and cannot identify from the present data. Immediate access to content, reduced administrative friction, and convenience effects are offered here only as a plausible post-hoc proposition for future research to test explicitly, not as an established mechanism; the autonomy-building process that Self-Determination Theory would predict, and that the learning-innovation pathway (H6) is consistent with, remains one candidate explanation among several this study cannot adjudicate. This distinction matters for how the two antecedents should be theorized going forward, though it should be stated precisely: this study has shown that the tested self-directed-learning mechanism explains learning innovation's association with perceived learning outcomes and does not explain digital competence's, not that it has identified what digital competence's alternative mechanism actually is. Learning innovation and digital competence are both associated with perceived learning outcomes, but the present data support only the claim that their tested mediation mechanisms differ, not the stronger claim that two complete, separately identified mechanisms are now on the table; treating them as interchangeable levers for building student autonomy would still be unsupported by the present evidence.

4.2.1 Theoretical Implications

Across all seven hypotheses, the results are more consistent with two structurally different pathways to perceived learning outcomes than with one shared mechanism, though only one of those two pathways has been positively identified. Learning innovation operates through both a direct channel and, on the evidence for H3 and H6, a self-directed-learning channel, a pattern consistent with Self-Determination Theory's account of how instructional design can shape learner autonomy. Digital competence's direct channel to perceived learning outcomes (H2) does not run through self-directed learning (H4, H7 unsupported), which rules out the specific mechanism this study tested rather than establishing what mechanism operates in its place; the null result is at least consistent with the cautionary literature on educational technology, including Gutu et al. (2024) and Bulman and Fairlie (2016), which argues digital access does not automatically cultivate independent learning behavior, but consistency with that literature is not the same as this study having identified digital competence's actual mechanism. Universities pursuing digital competence as a lever for building self-directed learners specifically, rather than for raising perceived learning outcomes through other means, should treat that link as an empirical question to test locally rather than a mechanism to assume.

This study's pattern of results is consistent with, though it does not directly test, Self-Determination Theory in a digitally mediated higher education setting. Because autonomy need satisfaction, competence, and relatedness were not measured, the significant learning-innovation-to-self-directed-learning path is equally consistent with alternative mechanisms this model did not distinguish, including engagement, cognitive activation, self-efficacy, or instructor support; it cannot be attributed to autonomy satisfaction specifically. What the data do show is that an instructional stimulus built around problem-based and interactive methods that hand control to the learner was associated with self-directed learning, while a stimulus built around access and infrastructure was not. Prior applications of Self-Determination Theory to educational technology have tended to treat digital tools as autonomy-supportive by default; the present pattern is compatible with the more cautious reading that autonomy support depends on how a stimulus is designed, but confirming that reading requires measuring the theory's psychological mechanisms directly in future work, which this study did not do.

The results also refine the emerging literature that treats self-directed learning as a general-purpose mediator between educational antecedents and student outcomes. Rashid and Asghar (2016) and Lee and Chang (2025) both established self-directed learning as a credible mediating mechanism, but neither tested whether that mediating role holds uniformly across different types of antecedents within the same model. By testing two structurally different antecedents side by side, learning innovation and digital competence, this study shows self-directed learning mediates one pathway and not the other within the same sample and the same measurement model. This antecedent-specific pattern argues against treating self-directed learning as an automatic mediator whenever it is included in a model, and instead supports testing its mediating role separately for each antecedent, consistent with the standalone mediation hypotheses (H6, H7) specified in Section 2 rather than inferring mediation from direct effects alone.

Finally, the null relationship between digital competence and self-directed learning provides an empirical test, in a management and higher education setting, of the caution Bulman and Fairlie (2016) raised in the economics of education literature: that technology's effect on learning behavior depends on how it is used, not on its availability. Combined with Gutu et al.'s (2024) finding that digitalization reduced learning engagement in a different national sample, the present result adds a second, independent data point suggesting the link between digital access and self-regulated learning behavior is not a stable universal effect and warrants continued empirical scrutiny rather than theoretical assumption in future PLS-SEM models of digital higher education.

4.2.2 Practical Implications

For university administrators, the clearest implication is that digital competence and learning innovation are not interchangeable levers and should not share a single budget line or a single success metric. Where the goal is raising perceived learning outcomes broadly, both investments are justified, since each showed a significant direct effect.Where the specific goal is building self-directed learners, capable of setting their own goals and managing their own study without constant supervision, this sample's pattern is consistent with pedagogical redesign, problem-based learning, flipped classrooms, and interactive teaching formats, mattering more than digital infrastructure access; because autonomy itself was not measured and the design is cross-sectional, this is offered as a hypothesis for institutions to test through their own pilots and experimentation, not as an established basis for reallocating budgets away from digital investment.

For curriculum designers and lecturers, learning innovation's strong relationship with self-directed learning suggests that redesigning how a course is taught carries more weight for building learner autonomy than which digital tools accompany it. Faculty development programs aimed at cultivating self-directed learners are therefore better targeted at pedagogical technique than at digital tool training alone.

For instructional technology teams and platform developers, the finding that digital competence reaches perceived learning outcomes directly rather than through self-directed learning implies that current platforms may be succeeding at convenience, immediate content access, streamlined administration, and communication, without necessarily teaching students to regulate their own learning. Institutions that want their digital platforms to also build self-directed learning should not assume this happens automatically; it likely requires deliberately embedding autonomy-supportive design features into the platform itself, such as self-set goals, progress dashboards students control, or guided reflection prompts, rather than treating access as sufficient on its own.

For student affairs and academic support units, the strong direct link between self-directed learning and perceived learning outcomes justifies standalone self-directed learning skill-building, workshops on goal-setting, time management, and independent study strategies, as a complementary intervention that does not depend on which digital or pedagogical investments an institution is currently making.

5. Conclusion and Suggestion

This study tested seven hypotheses linking learning innovation and digital competence, the latter operationalized as students' individual digital learning competence rather than institutional digital transformation, to perceived learning outcomes, directly and through self-directed learning as a mediator, among 312 undergraduate students recruited by purposive and snowball sampling at a single private university in Surabaya, Indonesia. The measurement model showed strong reliability, convergent validity, and discriminant validity within the limits discussed in Section 6, and the structural model showed moderate-to-substantial explanatory power and predictive performance superior to a naive benchmark under internal cross-validation; SRMR and NFI are reported as descriptive fit indices rather than as conclusive proof of model fit. Five of seven hypotheses were supported: learning innovation and digital competence were both significantly and positively associated with perceived learning outcomes directly (H1, H2); learning innovation was significantly associated with self-directed learning (H3); self-directed learning was significantly associated with perceived learning outcomes (H5); and self-directed learning significantly mediated the learning-innovation-to-outcome relationship (H6). Two hypotheses were not supported: digital competence was not significantly associated with self-directed learning (H4), and self-directed learning did not mediate the digital-competence-to-outcome relationship (H7). Because the design is cross-sectional and single-source, all of these statements describe associations consistent with the hypotheses, not confirmed causal effects.

The practical implication is that university administrators should not assume digital competence alone is associated with building self-directed learning; on this evidence, digital competence is associated with perceived learning outcomes through a mechanism this study did not directly measure, while pedagogical innovation shows the stronger association with student autonomy specifically. Because this is a cross-sectional, single-source design, none of the seven paths can be interpreted as strictly causal, and reciprocal or common-method explanations cannot be ruled out; replication with temporally or source-separated data, and in other institutional and cultural settings, is needed before generalizing the null digital-competence-to-self-directed-learning finding. Future work extending this model should incorporate Importance-Performance Map Analysis, which this study's methodology proposed but did not execute, so IPMA-based prioritization is not offered as a finding here.

These findings suggest concrete next steps for practice: university administrators should evaluate digital competence and learning innovation investments against separate objectives rather than a single perceived-learning-outcomes target, and should pilot autonomy-supportive features, such as student-controlled progress tracking and reflective prompts, within existing digital platforms before assuming those platforms already build self-directed learning. All recommendations here are offered as associational, context-specific guidance for this sample rather than as universally generalizable prescriptions.

6. Limitations and Future Research

Several limitations qualify every result in Section 4. Digital competence was operationalized with an individual-level scale (Song et al., 2025), not an instrument capturing institutional digital transformation; interpretation is aligned to what was measured, and findings should not be extended to institutional policy claims. Students were recruited through purposive and snowball sampling at a single private university without recording response rate, program, semester, demographic, or lecturer/course identifiers; because learning-innovation perceptions likely share a lecturer or course, some dependence among observations cannot be ruled out, and without intraclass correlations or cluster-robust estimation, standard errors may be somewhat optimistic. Common method bias cannot be fully excluded: the pilot Harman's test exceeded this study's own 50% threshold, the full-collinearity procedure (Kock & Lynn, 2012) was not run in full, and reciprocal causation, students who feel they learned more rating every construct more favorably, remains plausible; Section 4 therefore uses associational rather than causal language throughout. Item SDL7 was dropped without a pre-registered criterion, and its original loading and wording are not reported; composite reliability above .90 for every construct also raises the possibility of item redundancy, and item-level correlations and rho_A were not reported in Table 1. Finally, the predictive results demonstrate internal validity only, not external generalizability, and Importance-Performance Map Analysis was not executed despite being part of the original design. Together, the conclusions in Section 6 should be read as associations specific to this single-university sample, not generalized causal claims about Indonesian higher education.

Future research should incorporate Importance-Performance Map Analysis to prioritize intervention points, measure institutional digital transformation directly alongside individual digital competence so the two levels are no longer conflated, report full respondent profiles and test for clustering explicitly, and pursue qualitative or mixed-methods work to explain why digital competence did not significantly associate with self-directed learning here.

Acknowledgement

The authors thank the participating students and the host university for their cooperation during data collection. This research received no external funding.

Declaration of AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) used perplexity. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Reference

Bhuttah, T. M., Xusheng, Q., Abid, M. N., & Sharma, S. (2024). Enhancing student critical thinking and learning outcomes through innovative pedagogical approaches in higher education: The mediating role of inclusive leadership. Scientific Reports, 14(1), 24362. https://doi.org/10.1038/s41598-024-75379-0

Bulman, G., & Fairlie, R. W. (2016). Technology and education: Computers, software, and the internet. In E. A. Hanushek, S. Machin, & L. Woessmann (Eds.), Handbook of the Economics of Education (Vol. 5, pp. 239–280). Elsevier. https://doi.org/10.1016/B978-0-444-63459-7.00005-1

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, 11(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Fisher, M., King, J., & Tague, G. (2001). Development of a self-directed learning readiness scale for nursing education. Nurse Education Today, 21(7), 516–525. https://doi.org/10.1054/nedt.2001.0589

Gudergan, S. P., Ringle, C. M., Wende, S., & Will, A. (2008). Confirmatory tetrad analysis in PLS path modeling. Journal of Business Research, 61(12), 1238–1249. https://doi.org/10.1016/j.jbusres.2008.01.012

Gutu, I., Medeleanu, C. N., & Asiminei, R. (2024). The limits of learning engagement and academic leadership within the higher education digitalization process: Analysis by using PLS SEM. PLOS ONE, 19(11), e0306079. https://doi.org/10.1371/journal.pone.0306079

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. Information Systems Journal, 28(1), 227–261. https://doi.org/10.1111/isj.12131

Kock, N., & Lynn, G. S. (2012). Lateral collinearity and misleading results in variance-based SEM: An illustration and recommendations. Journal of the Association for Information Systems, 13(7), 546–580. https://doi.org/10.17705/1jais.00302

Lee, D. C., & Chang, C. Y. (2025). Evaluating self-directed learning competencies in digital learning environments: A meta-analysis. Education and Information Technologies, 30(6), 6847–6868. https://doi.org/10.1007/s10639-024-13083-2

Liengaard, B. D., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2021). Prediction: Coveted, yet forsaken? Introducing a cross-validated predictive ability test in partial least squares path modeling. Decision Sciences, 52(2), 362–392. https://doi.org/10.1111/deci.12445

Rashid, T., & Asghar, H. M. (2016). Technology use, self-directed learning, student engagement and academic performance: Examining the interrelations. Computers in Human Behavior, 63, 604–612. https://doi.org/10.1016/j.chb.2016.05.084

Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results: The importance-performance map analysis. Industrial Management & Data Systems, 116(9), 1865–1886. https://doi.org/10.1108/IMDS-10-2015-0449

Song, Y., Lv, S., Wang, M., Wang, Z., & Dong, W. (2025). The impact of digital learning competence on the academic achievement of undergraduate students. Behavioral Sciences, 15(7), 840. https://doi.org/10.3390/bs15070840

Sun, T., & Yoon, M. (2025). The impact of digital transformation on faculty performance in higher education: The mediating role of digital self-efficacy and the moderating role of task-technology fit. Frontiers in Psychology, 16, 1693375. https://doi.org/10.3389/fpsyg.2025.1693375

Zakir, S., Hoque, M. E., Susanto, P., Nisaa, V., Alam, M. K., Khatimah, H., & Mulyani, E. (2025). Digital literacy and academic performance: The mediating roles of digital informal learning, self-efficacy, and students' digital competence. Frontiers in Education, 10, 1590274. https://doi.org/10.3389/feduc.2025.1590274

Zhao, X., Lynch, J. G., Jr., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. Journal of Consumer Research, 37(2), 197–206. https://doi.org/10.1086/651257