PERCEIVED DIGITAL INTERACTIVE LEARNING MEDIA AND MOTIVATION AS OVERLAPPING CORRELATES OF SELF-REPORTED ECONOMICS OUTCOMES

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ABSTRACT
Digital learning experiences and student motivation are frequently modeled as distinct correlates, although their measures may capture overlapping perceptions. This study examined the bivariate and joint associations of perceived digital interactive learning media and learning motivation with self-reported economics outcomes among Grade 10 students at one Indonesian secondary school. A cross-sectional survey analyzed 106 students from a population of 144; the source record identified simple random sampling but did not document randomization, participant demographics, or non-response. Three 15-item summed Likert scales were used. Internal consistency was exceptionally high (Cronbach's alpha = .981-.983), warranting caution regarding redundancy and discriminant validity. Simple regressions showed strong associations for digital media (beta = .832, R-squared = .693, p < .001) and motivation (beta = .833, R-squared = .694, p < .001). The joint model was significant, F(2, 103) = 118.313, p < .001, R-squared = .697, but unique coefficients were not significant for digital media, B = .396, 95% CI [-.372, 1.164], p = .308, or motivation, B = .437, 95% CI [-.325, 1.199], p = .258. The increment beyond the stronger single-predictor model was only delta R-squared = .003. The pattern is compatible with substantial shared variance, overlapping item content, or common-method effects and does not establish an integrated mechanism or causal influence. The study offers a school-specific diagnostic for refining measurement and digital pedagogy. Future research should report complete sampling and ethics procedures, use objective achievement data and non-overlapping validated scales, and provide multicollinearity, residual, and longitudinal or experimental evidence.

Keywords: digital interactive learning media, economics education, learning motivation, secondary education, self-reported economics outcomes

INTRODUCTION

In the past decade, much research has focused on how digital technologies can improve the quality, reach, and responsiveness of teaching. Interactive video, simulation, mobile applications, digital games, and adaptive platforms can provide multimodal representations, immediate feedback, repeated practice, and learner control. These affordances are particularly relevant when students must understand abstract relationships rather than merely reproduce facts. Meta-analytic evidence generally indicates that technology-supported instruction can improve learning, but the magnitude of the benefit varies substantially according to pedagogical design, subject area, learner age, implementation quality, and the comparison condition (Chauhan, 2017; Hillmayr et al., 2020; Sung et al., 2016; Tamim et al., 2011; Tingir et al., 2017). Consequently, the central question is no longer whether a digital device is present in a classroom, but whether the technology creates meaningful cognitive activity and sustained engagement.

The distinction between access and pedagogical quality is important for secondary schools in digitally expanding education systems. A computer laboratory, internet connection, projector, or learning-management platform does not automatically produce active learning. Reviews of educational technology show that positive effects are more likely when tools are aligned with learning objectives, embedded in structured tasks, accompanied by feedback, and used to elicit explanation, practice, or problem solving (Cheung & Slavin, 2012, 2013; Fiorella & Mayer, 2016; Moreno & Mayer, 2007). Digital games and gamified activities can also support cognitive and motivational outcomes, although poorly aligned reward structures or excessive visual complexity may distract learners from the disciplinary content (Clark et al., 2016; Sailer & Homner, 2020; Wouters et al., 2013; Yu, 2019). Thus, interactive media should be understood as an instructional design environment, not as a neutral delivery channel. Recent reviews further show that technology-supported learning depends on self-regulation and the social climate surrounding technology use, not merely on platform availability (Goagoses et al., 2024; Prasse et al., 2024).

Economics is a suitable domain for investigating this issue because many of its core concepts involve systems, trade-offs, feedback loops, and dynamic relations. Supply and demand, inflation, market equilibrium, fiscal policy, opportunity cost, and financial-market behavior are often difficult to grasp through verbal exposition alone. Interactive graphs, scenario-based simulations, short explanatory videos, and immediate-response quizzes can make changes in economic variables visible and allow students to test consequences. Research in economics education has repeatedly called for movement beyond lecture-dominated instruction and toward active, technology-supported learning (Allgood et al., 2015; Becker & Watts, 2001). Studies of flipped and digitally supported economics courses have reported benefits under some conditions, but findings are not uniformly positive, and most evidence comes from higher education rather than secondary schools (Asarta, 2024; Balaban et al., 2016; Calimeris, 2018; Calimeris & Sauer, 2015; Caviglia-Harris, 2016; Goffe, 2024; Wozny et al., 2018).

Student motivation is treated as the primary psychological framework in this study. Self-determination theory explains why autonomy, competence, and relatedness can sustain high-quality engagement, while expectancy-value theory clarifies how expectations of success and perceived task value influence effort (Deci & Ryan, 2000; Eccles & Wigfield, 2002; Ishida & Sekiyama, 2024; Ryan & Deci, 2020). Multimedia and generative-learning perspectives are used as complementary task-design accounts: digital features can support motivation only when they organize information, provide meaningful choices and feedback, and elicit explanation or application (Fiorella & Mayer, 2016; Moreno & Mayer, 2007). This hierarchy of frameworks avoids treating several compatible theories as if all were directly tested.

Recent Indonesian evidence also indicates that technology-related experiences should be modeled together with motivational or self-regulatory mechanisms. Ibrahim et al. (2026), for example, examined interactive modules, learning autonomy, and self-directed learning among Jakarta middle-school students using validated measures and multivariate modeling. That study explicitly tested a mechanism, whereas the present study uses cross-sectional regression and cannot test mediation, interaction, or reciprocal influence. Its narrower contribution is to determine whether the two survey predictors provide distinct information or mostly overlapping associations in secondary economics.

The local problem was identified at SMA Negeri 1 Tompaso in Minahasa Regency, North Sulawesi. Preliminary information indicated that the school had a computer laboratory and stable internet access, while genuinely interactive classroom use remained limited. The previously cited daily-test average of 65, below the mastery criterion of 75, served only as contextual motivation and was not the dependent variable analyzed in this study. The available record does not identify the specific digital tools, frequency of use, economics topics, teacher characteristics, device access, or socioeconomic and connectivity profile. Accordingly, the study should be read as a school-specific diagnostic of student perceptions rather than an evaluation of a defined digital intervention or objective economics achievement. This distinction is consistent with recent synthesis showing that objective achievement and subjective academic experiences are related but analytically different outcomes in secondary education (Costa et al., 2024).

Within the literature reviewed for this manuscript, prior studies mainly follow separate streams: technology-supported instruction, student motivation, or digitally mediated economics learning. Less attention has been given to whether perceptions of digital media and motivation remain empirically distinguishable when measured simultaneously in secondary economics.

This issue is consequential because overlapping item content and same-source self-reporting can create very high zero-order correlations without demonstrating independent explanatory effects (Podsakoff et al., 2003). The research gap is therefore both substantive and measurement-related: the study examines shared versus unique association while explicitly testing the limits of interpretation.

To address this gap, the study compares two bivariate regressions with a multiple regression, reports incremental explained variance and confidence intervals derived from the reported coefficients, and distinguishes set-level significance from unique partial effects. The analysis does not demonstrate that digital media and motivation form an integrated mechanism; such a mechanism remains one plausible theoretical interpretation alongside construct overlap and common-method variance. This bounded analytical purpose strengthens transparency and prevents causal or mechanistic claims that the design cannot support.

Digital interactive learning media refers here to technology-based resources that allow learners to respond, manipulate representations, receive feedback, make choices, or navigate content rather than merely view static information. Cognitive theories of multimedia learning emphasize the need to coordinate verbal and visual information without overloading working memory, while interactive multimodal environments can promote deeper processing when students select, organize, integrate, and apply information (Moreno & Mayer, 2007). Generative learning further suggests that students learn more durably when they explain, map, visualize, enact, or otherwise produce meaning from content (Fiorella & Mayer, 2016). Therefore, interactivity is valuable only when it elicits disciplinary thinking.

Large research syntheses support a generally positive but conditional role for technology. Tamim et al. (2011) found an overall advantage for technology-supported instruction across decades of research, while later meta-analyses showed that effects depend on context, implementation, and tool characteristics (Chauhan, 2017; Hillmayr et al., 2020; Sung et al., 2016; Tingir et al., 2017). In K-12 mathematics and reading, educational technology applications have produced stronger outcomes when they supplement structured instruction rather than function as unintegrated add-ons (Cheung & Slavin, 2012, 2013). These findings support H1 but also caution against interpreting students' positive perceptions of media as proof of instructional effectiveness.

In economics education, technology can visualize relationships and create opportunities for active learning. Yet studies of flipped classrooms illustrate the importance of instructional architecture. Some courses report improved outcomes or engagement when students use videos and online materials before class and spend class time solving problems (Balaban et al., 2016; Calimeris & Sauer, 2015; Caviglia-Harris, 2016). Other evaluations show small, mixed, or schedule-dependent effects (Calimeris, 2018; Wozny et al., 2018). This variation indicates that digital access must be coupled with clear expectations, feedback, active tasks, and alignment between online and classroom components. Contemporary economics-education guidance similarly emphasizes deliberate practice, interaction, and pedagogical purpose when selecting technologies (Asarta, 2024; Goffe, 2024).

Learning motivation refers to the internal and external processes that initiate, direct, and sustain learning behavior. Under self-determination theory, autonomous motivation is more likely when students experience meaningful choice, competence-supportive feedback, and supportive relationships (Deci & Ryan, 2000; Ryan & Deci, 2020). Expectancy-value theory adds that effort depends on expectations for success and perceived task value (Eccles & Wigfield, 2002). Across educational contexts, motivation is associated with engagement and achievement, and interventions that enhance relevance, goal clarity, or adaptive beliefs can produce meaningful educational benefits (Howard et al., 2021; Ishida & Sekiyama, 2024; Lazowski & Hulleman, 2016; Wijnia et al., 2024). These foundations support H2.

The conceptual model therefore treats perceived digital interactive learning media (DILM; X1) and learning motivation (X2) as concurrent correlates of self-reported outcomes (Y). Under the primary self-determination framework, perceived digital affordances may be experienced as competence-, autonomy-, or relevance-supportive, while motivation reflects students' interest, persistence, goals, response to challenge, and independent learning. However, the questionnaire indicators only partially operationalize these theory-specific processes, and the present regression models do not test mediation or interaction. H3 consequently concerns the significance of the predictor set, not independent effects by both variables.

Accordingly, the purpose of this study was to examine the bivariate and joint associations of DILM and learning motivation with self-reported economics outcomes among Grade 10 students at SMA Negeri 1 Tompaso. H1 and H2 predicted positive bivariate associations, while H3 predicted that the two-variable set would explain significant outcome variance. The study's novelty is the explicit separation of bivariate predictive strength, incremental explained variance, and unique partial contribution in an underrepresented secondary economics context. The scope is limited to one school, one grade level, one cross-sectional period, and questionnaire-based constructs. The study therefore provides a school-specific diagnostic and an exploratory test of overlapping associations; it does not establish causal effects, intervention efficacy, a mediation mechanism, or objective academic achievement.

METHOD

Research Design and Approach

The study used a quantitative, cross-sectional survey design to estimate relationships among DILM, learning motivation, and self-reported economics outcomes at one point in time. No treatment was assigned and no pretest-posttest comparison was conducted; therefore, association and prediction are used instead of causal effect. The original analysis was conducted with IBM SPSS Statistics version 23. A sensitivity calculation based on n = 106, alpha = .05, two predictors, and 80% power indicates that the overall regression could detect approximately f-squared = .094. This post hoc sensitivity estimate does not replace a design-stage power analysis tied to prespecified hypotheses.

Population and Participants

The target population comprised 144 Grade 10 students distributed across five classes, and the research record labels the selection of 106 participants as simple random sampling. However, the sampling frame, random-number procedure, class-level allocation, eligibility criteria, recruitment process, response rate, exclusions, and demographic characteristics were not documented. All 106 responses were reported as included in the analysis, but the absence of participant-flow and demographic information prevents independent reproduction of the sampling procedure and precludes construction of a demographic table.

Study Context and Transferability

The available record describes computer-laboratory and internet access alongside limited use of genuinely interactive learning activities. It does not document the platforms used, frequency or duration of use, economics topics, teacher experience, instructional arrangement, student device access, or home connectivity. The study is therefore positioned as a school-specific diagnostic and an exploratory test of a general association pattern. Transfer to other schools requires caution because readers cannot compare key contextual conditions.

Data Collection and Instruments

The analyzed data were obtained from closed questionnaires. Although earlier materials mentioned classroom observation, no observation protocol, observer information, coding procedure, reliability evidence, or observational findings were available; observation was therefore removed as an analyzed data source. Three 15-item scales were scored from 1 (strongly disagree) to 5 (strongly agree), and the reported theoretical range of 15-75 indicates that item responses were summed. DILM (X1) covered content alignment, visual design, usability, interactive features, and perceived motivational impact. Learning motivation (X2) covered interest, perseverance and effort, learning goals, response to challenge, and independent learning. Self-reported economics outcomes (Y) covered cognitive, affective, and psychomotor perceptions. The complete item wording, original scale sources, adaptation procedures, content validation, pilot testing, reverse coding, and missing-item rules were not available. Consequently, treatment of partially completed questionnaires cannot be reproduced, and Y must not be equated with official test performance.

The operationalization only partially aligns with the organizing theories. DILM primarily captures perceived task and design affordances, whereas the motivation scale captures broad motivational behaviors rather than distinct self-determination or expectancy-value subscales. Moreover, the DILM indicator concerning motivational impact overlaps directly with X2. This built-in overlap requires factor-analytic evidence before the predictors can be interpreted as empirically distinct constructs.

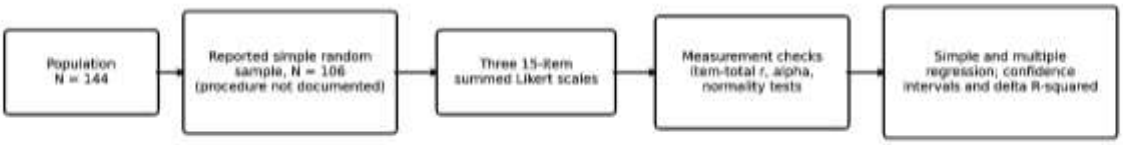

Figure 1. Revised research procedure and analytical transparency sequence

Validity and Reliability

Item-total correlations ranged from .853 to .922 for DILM, .799 to .946 for learning motivation, and .852 to .943 for self-reported outcomes, all above the reported critical value of .195. Cronbach's alpha was .982, .983, and .981, respectively. These values indicate high internal consistency but may also reflect redundant wording or narrow construct coverage (Sijtsma, 2009; Tavakol & Dennick, 2011). Because the complete instruments and raw data were unavailable, the manuscript cannot report expert content-validation procedures, exploratory or confirmatory factor analysis, composite reliability, average variance extracted, or discriminant-validity criteria. The reported reliability evidence therefore does not establish that X1, X2, and Y are distinct constructs.

Data Analysis

The analysis proceeded through frequency review, item and scale reliability checks, normality tests, two simple regressions, and one multiple regression. Kolmogorov-Smirnov tests with Lilliefors correction yielded $p = .200$ for all variables, whereas Shapiro-Wilk tests yielded $p = .003$. The regression estimates were retained but interpreted cautiously. Ninety-five percent confidence intervals were calculated from the reported unstandardized coefficients and standard errors. Incremental explanatory value was assessed by comparing the joint R-squared with each single-predictor R-squared. The source record did not contain the X1-X2 correlation, tolerance, variance inflation factors, condition indices, residual plots, linearity or homoscedasticity diagnostics, influence statistics, outlier rules, or missing-data procedures. Raw data were unavailable, so robust or bootstrap re-estimation and factor-analytic common-method checks could not be conducted. Predictor redundancy is therefore a plausible but incompletely quantified interpretation (O'Brien, 2007).

Ethical Considerations

The available research record did not identify an ethics committee, approval or exemption number, school authorization, parental or guardian permission, student assent or consent, voluntariness and withdrawal procedures, or a complete confidentiality protocol. Because the participants were school students and may have been minors, these omissions are publication-critical. No ethical approval is claimed in this manuscript. Before publication, the authors must verify and report the applicable institutional review, school permission, guardian permission, student assent or consent, confidentiality safeguards, and procedures for minimizing coercion. The analytical report contained no directly identifying student information.

Data Governance and Reproducibility

The source record did not provide a data-management plan, access controls, secure-storage procedures, retention and deletion schedules, a de-identified dataset, statistical syntax, a data dictionary, or complete software output. The score-range inconsistencies and duplicated frequency distributions must be reconciled against the original data before publication. Subject to ethical restrictions, the authors should archive the questionnaire, codebook, analysis syntax, and de-identified data or provide a justified controlled-access statement.

RESULTS AND DISCUSSION

Measurement Quality and Assumption Checks

The analyzed sample consisted of 106 students. Each construct was represented by 15 questionnaire items, and the scales were reported as summed scores with a theoretical range of 15-75. The reported empirical scores ranged from 33 to 75. However, the grouped frequency table extended to 78 and reproduced the same seven-class distribution for all three constructs. Because these inconsistencies may reflect transcription or table-copying errors, the duplicated distributions are not used substantively. Scale means, standard deviations, the full correlation matrix, response rates, and item-level missingness were not available in the source record and therefore cannot be reported without the original data.

Measurement statistics were strong at the item and scale levels. All reported item-total correlations exceeded the critical value, and alpha coefficients were above .98. These results indicate that students responded consistently to the items within each scale. Nevertheless, extremely high alpha values warrant caution because near-duplicate items can inflate reliability while narrowing construct coverage. In this study, the concern is substantive as well as statistical: perceived media quality included a motivational-impact component, while motivation was modeled as a separate predictor.

The Kolmogorov-Smirnov statistics were .058 for DILM, .054 for learning motivation, and .061 for self-reported outcomes, with $p = .200$ in each case. The corresponding Shapiro-Wilk statistics were .961, .960, and .960, with $p = .003$. Thus, the tests produced different decisions. With $n = 106$, ordinary least squares estimates may remain informative under moderate deviations, but the absence of residual, heteroscedasticity, influence, and outlier diagnostics limits assessment of model adequacy.

Table 1. Instrument quality and reported normality diagnostics

Variable	Items	Item-total r	Cronbach's α	K–S	K–S p	S-W statistic / p
Perceived digital interactive learning media (DILM; X1)	15	.853–.922	.982	.058	.200	.961 / .003
Learning motivation (X2)	15	.799–.946	.983	.054	.200	.960 / .003
Self-reported outcomes (Y)	15	.852–.943	.981	.061	.200	.960 / .003

Note. DILM = perceived digital interactive learning media; K-S = Kolmogorov-Smirnov; S-W = Shapiro-Wilk. The complete item wording, factor structure, means, standard deviations, and full correlation matrix were unavailable.

Bivariate Relationships and Joint Model

H1 was supported only as a bivariate association. DILM was strongly and positively associated with self-reported economics outcomes: Y = 6.761 + 0.832X1, B = .832, SE = .054, 95% CI [.725, .939], beta = .832, t = 15.319, p < .001. The model yielded R = .832, R-squared = .693, adjusted R-squared = .690, F(1, 104) = 234.671, p < .001, and a standard error of estimate of 6.970. These statistics describe association, not the effect of a defined digital intervention.

H2 was likewise supported only as a bivariate association. Learning motivation was strongly and positively associated with self-reported economics outcomes: Y = 6.326 + 0.827X2, B = .827, SE = .054, 95% CI [.720, .934], beta = .833, t = 15.345, p < .001. The model yielded R = .833, R-squared = .694, adjusted R-squared = .691, F(1, 104) = 235.458, p < .001, and a standard error of estimate of 6.962.

H3 was supported for the predictor set. The multiple model yielded R = .835, R-squared = .697, adjusted R-squared = .691, F(2, 103) = 118.313, p < .001, and a standard error of estimate of 6.960. Relative to the stronger motivation-only model, the incremental explained variance was only delta R-squared = .003; relative to the DILM-only model, it was .004. Thus, the overall model was significant, but the addition of the second highly overlapping predictor produced minimal incremental information.

The unique coefficients were not statistically significant. DILM had B = .396, SE = .387, 95% CI [-.372, 1.164], beta = .397, t = 1.025, p = .308; learning motivation had B = .437, SE = .384, 95% CI [-.325, 1.199], beta = .440, t = 1.137, p = .258. Both confidence intervals included zero. The data therefore support strong bivariate associations and a significant predictor set, but they do not support independent contributions by either predictor after shared variance is controlled.

Table 2. Regression model summary

Model	R	R^2	Adjusted R^2	SEE	F (df)	p
DILM predicting Y	.832	.693	.690	6.970	234.671 (1, 104)	< .001
X2 predicting Y	.833	.694	.691	6.962	235.458 (1, 104)	< .001
DILM and X2 predicting Y	.835	.697	.691	6.960	118.313 (2, 103)	< .001

Table 3. Regression coefficients and hypothesis interpretation

Model	Predictor	B	SE	β	t	p
Simple	DILM (X1)	.832	.054	.832	15.319	< .001
Simple	X2	.827	.054	.833	15.345	< .001
Multiple	DILM (X1)	.396	.387	.397	1.025	.308
Multiple	X2	.437	.384	.440	1.137	.258

Perceived Digital Interactive Learning Media and Self-Reported Economics Outcomes

The strong bivariate association between DILM and self-reported economics outcomes is consistent with research showing that technology can support learning when it makes content visible, responsive, and actionable. Interactive graphs, market simulations, animations, and feedback-rich quizzes may help students coordinate dynamic economic relationships. This interpretation aligns with multimedia and generative-learning perspectives, but the present survey measures perceptions of the learning environment rather than exposure to a standardized digital treatment (Fiorella & Mayer, 2016; Moreno & Mayer, 2007).

The finding is also broadly consistent with meta-analytic evidence on technology-supported instruction and with recent Indonesian work linking interactive modules with autonomy and self-directed learning (Chauhan, 2017; Goffe, 2024; Hillmayr et al., 2020; Ibrahim et al., 2026; Sung et al., 2016; Tamim et al., 2011). Nevertheless, the coefficient cannot be interpreted as an intervention effect. Students who evaluated the digital environment favorably also evaluated their learning outcomes favorably, and the design cannot determine temporal ordering or exclude teacher quality, prior achievement, access, or general positive response tendencies.

Accordingly, the direct implication is limited: the school should examine which digital features students perceive as usable, interactive, and aligned with economics content. Suggestions concerning simulations, predictive tasks, or feedback cycles are literature-informed design options rather than interventions evaluated by this study. Their effectiveness should be tested with objective achievement measures and documented implementation fidelity.

Learning Motivation and Self-Reported Economics Outcomes

The strong bivariate association between learning motivation and self-reported economics outcomes is theoretically plausible. Interest, persistence, goal direction, response to challenge, and independent learning can support sustained cognitive work. The pattern is consistent with self-determination and expectancy-value perspectives and with meta-analytic evidence relating motivation to engagement and achievement (Eccles & Wigfield, 2002; Howard et al., 2021; Ishida & Sekiyama, 2024; Lazowski & Hulleman, 2016; Ryan & Deci, 2020; Wijnia et al., 2024). However, the scale did not isolate autonomous motivation, controlled motivation, expectancy, or value as distinct theory-specific dimensions.

Motivation should therefore be interpreted as a broad self-reported orientation rather than enthusiasm alone. Teachers may support autonomy through bounded choices, competence through progressive challenge and informative feedback, and relevance through local economic cases. These recommendations are theoretically grounded but were not tested as interventions in this study. Utility-value research suggests that connecting academic ideas to students' lives can strengthen interest and performance, yet transfer to this school requires direct evaluation (Hulleman & Harackiewicz, 2009; Hulleman et al., 2010).

The observed association does not establish that motivation caused stronger outcomes. Perceived success may increase confidence and interest, while teacher support, prior achievement, family expectations, digital access, and peer norms may influence both variables. Longitudinal and experimental evidence is required to establish temporal sequence or intervention effectiveness.

Shared Variance and Limited Unique Effects

The central result is the contrast between the simple and multiple regressions. Each predictor alone explained approximately 69% of outcome variance, while the joint model explained 69.7%. The incremental gain was only .003-.004, and neither unique coefficient was significant. This pattern indicates that DILM and motivation conveyed nearly the same predictive information about Y in the available measures.

One explanation is substantive: students may experience an interactive environment and their motivation as closely connected aspects of engagement. However, this explanation was not tested. Equally plausible explanations include overlapping item content, because the DILM scale includes motivational impact; same-source and same-format response tendencies; or an unmeasured factor such as teacher support. The evidence is therefore compatible with an engagement-system proposition but does not demonstrate that mechanism.

The pattern also strongly suggests predictor redundancy, yet multicollinearity was not quantified because the X1-X2 correlation, tolerance, variance inflation factors, condition indices, and raw data were unavailable. The confidence intervals for both unique coefficients included zero. A complete reanalysis should report the correlation matrix, VIF and tolerance, residual and influence diagnostics, heteroscedasticity-robust or bootstrap intervals, and competing factor models (O'Brien, 2007).

The statistical interpretation must therefore remain precise. $R = .835$ is a multiple correlation, whereas R-squared = .697 represents 69.7% explained variance. A significant overall F test shows that the predictor set improves prediction relative to an intercept-only model; it does not show that both predictors make independent contributions. In this study, the set-level test was significant, but both partial tests were non-significant.

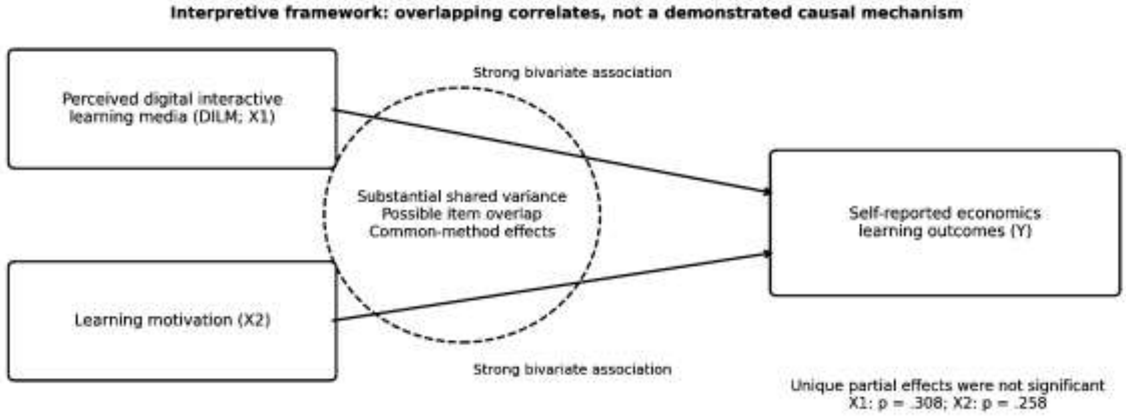

Figure 2. Interpretive framework for shared and unique associations

Theoretical Contribution and Boundaries

The study's contribution is methodological and conceptual rather than causal. It shows that theoretical integration must be accompanied by measurement differentiation: when a media-quality scale already includes motivational impact, entering it beside a motivation scale blurs environmental affordance and psychological response. The primary self-determination framework provides a rationale for why digital features may support motivation, while multimedia and generative learning describe how task design may support cognitive processing. The present measures, however, do not directly test those mechanisms.

A stronger future model would separate observable digital features, theory-specific motivational processes, and objective achievement. Confirmatory factor analysis could test whether a three-factor structure is distinguishable from one- or two-factor alternatives, and structural equation modeling could evaluate mediation only after discriminant validity is established. The current evidence supports a proposition of overlapping perceptions, not a verified integrated engagement system.

Bounded Practical and Policy Implications

The direct practical implication is diagnostic: teachers and school leaders should examine whether digital learning activities are perceived as aligned, usable, interactive, and motivationally supportive. The study does not identify which platform or activity caused better outcomes. Literature-informed lesson designs may combine a relevant economic problem, prediction, interactive representation, feedback, and explanation, but these should be piloted and evaluated rather than presented as proven consequences of the survey.

At the school level, the contextual record suggests that infrastructure availability alone may not guarantee pedagogically interactive use. Professional development, technical support, and instructional coaching are reasonable implementation options derived from the broader literature. Their necessity and effectiveness at SMA Negeri 1 Tompaso were not directly measured, so recommendations should remain conditional and should include implementation evidence, teacher perspectives, and equitable access checks. This position is also consistent with evidence that technology-supported self-regulation requires coordinated pedagogical scaffolding rather than isolated digital features (Prasse et al., 2024).

System-level policy conclusions are not warranted from one school's self-reported survey. A defensible policy implication is narrower: future evaluation of digital economics learning should combine objective concept tests, performance tasks, observed engagement, validated motivational measures, and implementation data. This multi-source approach would reduce common-method risk and make policy decisions more evidence-based. Attention to classroom climate and student voice is also important when technology changes the social organization of learning (Goagoses et al., 2024).

A phased school-level pilot is therefore preferable to immediate scaling. One economics unit can be designed with explicit learning goals, a documented interactive activity, access accommodations, and pre-specified outcome measures. Student work, objective assessment, and implementation feedback can then guide revision before broader adoption.

Limitations and Future Research

The non-significant partial coefficients are the most informative and unexpected result. They show that strong bivariate models do not establish two independent effects. The evidence is sufficient to describe strong associations in this sample, but not to assign causal importance to either predictor or to claim that a shared engagement mechanism has been empirically demonstrated.

The study is limited by one school and grade level, cross-sectional timing, same-source self-report measures, an outcome that is not an objective economics test, incomplete sampling and demographic documentation, limited contextual description, exceptionally high alpha coefficients, mixed normality tests, absent multicollinearity and residual diagnostics, duplicated frequency distributions, unavailable raw data, and unverified ethics and consent procedures. These limitations materially constrain reproducibility, construct validity, and transferability. Recent synthesis of secondary-school achievement likewise supports treating motivational, instructional, and contextual factors as interdependent rather than as isolated causes (Costa et al., 2024).

The immediate analytical priority is to reconcile the source dataset and output, publish the complete instruments and scoring rules, report means, standard deviations, correlations, missing-data procedures, VIF and tolerance, residual and influence diagnostics, and test competing measurement models. Objective economics scores should be added to establish criterion validity and reduce reliance on common-method self-reporting.

Subsequent studies should use multi-school samples with documented contextual and demographic variation, preregistered hypotheses, longitudinal designs to establish temporal ordering, and experimental or quasi-experimental comparisons of defined digital activities. Only after measurement separation is demonstrated should mediation, interaction, or reciprocal models be tested.

CONCLUSION

This study examined the bivariate and joint associations of perceived digital interactive learning media and learning motivation with self-reported economics outcomes among Grade 10 students at SMA Negeri 1 Tompaso. Both predictors showed very strong bivariate associations, and the overall two-predictor model explained 69.7% of observed variance; however, the additional explained variance was only .003-.004 and neither unique coefficient was significant. The principal contribution is therefore a more precise account of overlapping predictive information, not evidence that two independent causes or an integrated engagement mechanism were established. For practice, the results justify careful school-level diagnosis and pilot testing of digital and motivational supports, while broader policy recommendations remain tentative. Future research should verify ethics and sampling procedures, use objective achievement measures and non-overlapping validated instruments, report complete diagnostics and reproducible data materials, and employ multi-site longitudinal or experimental designs.

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