ETDC Indonesian Journal of Research and Educational Review
Volume 6, No. 1, 2026, pp 238 - 249
e–ISSN 2809-3682
p–ISSN 2809-7505
https://doi.org/10.51574/ijrer.v6i1.5422

Synergizing Student Motivation and Project-Based Learning Syntax for Internet of Things Course Learning Outcomes

Chiwi Handayani[1], Matasia[2], Muh. Ma'ruf Idris[3]
[1, 2, 3] Department of Electronics Engineering and Information Technology, Universitas Negeri Makassar, Indonesia

Article Info

Article history:

Received June 01, 2026
Accepted August 28, 2026
Published September 04, 2026

Keywords:

Internet of Things;
Learning Motivation;
Project-Based Learning;
Psycho-Pedagogical Synergy;
Technical Engineering Education.

ABSTRACT

This study examines how internal learning motivation interacts with students' evaluative perception of Project-Based Learning (PjBL) syntax to influence academic achievement in a hardware-software integrated Internet of Things (IoT) course. A quantitative causal-associative survey design was executed among 48 Electronics Engineering Education students (2022 cohort) at Universitas Negeri Makassar using saturated total sampling. Data was collected via a validated 26-item Likert questionnaire and standardized rubrics evaluating cognitive, psychomotor, and effective IoT course performance. Analysis employed multiple linear regression preceded by classical assumption verifications, Harman's Single-Factor test for common method variance, and a G*Power post-hoc sensitivity check. Both learning motivation ($\beta = .308$, $t(45) = 2.308$, $p = .026$) and perception of PjBL syntax implementation ($\beta = .304$, $t(45) = 2.272$, $p = .028$) exerted significant positive partial effects on IoT learning outcomes. Jointly, the model demonstrated a significant simultaneous effect, $F(2, 45) = 5.644$, $p = .007$, accounting for 20.1% of achievement variance ($R^2 = .201$, Adjusted $R^2 = .165$). Post-hoc power analysis confirmed adequate statistical power ($1 - \beta = 0.812$, $\alpha = .05$) despite the small cohort size.

Corresponding Author:

Chiwi Handayani,
Department of Electronics Engineering and Information Technology, Universitas Negeri Makassar, Indonesia
Email: chiwihandayani5@gmail.com

1. INTRODUCTION

The rapid diffusion of Industry 4.0 paradigms across global manufacturing and infrastructure sectors has created an unprecedented demand for engineering graduates equipped with advanced capabilities in frontier technologies, particularly the Internet of Things (IoT) (Hernandez-de-Menendez et al., 2020; Stadnicka et al., 2022). IoT represents a complex technological ecosystem integrating sensor-actuator hardware, embedded microcontrollers, network communication protocols, cloud data telemetry, and software algorithm development (Pande et al., 2026). Consequently, higher education engineering programs must transcend traditional lecture-based instructional methodologies to cultivate both deep technical mastery and the psychological resilience necessary to navigate multi-layered system architectures (Winkens et al., 2024; Wint & Direito, 2026).

Despite the recognized importance of IoT competencies, instructional implementation in technical undergraduate programs frequently encounters profound pedagogical hurdles (Du et al., 2021; Gumina et al., 2024). Empirical diagnostic observations during the 2025/2026 academic cycle within the Department of Electronics Engineering and Information Technology at *Universitas Negeri Makassar* (UNM) highlighted systemic learning bottlenecks. Specifically, 62.5% of enrolled students exhibited severe difficulties in bridging theoretical networking concepts with hardware prototyping, encountering recurring obstacles during sensor calibration, microcontroller pin mapping, micro-Python script debugging, and MQTT protocol configuration. Furthermore, project evaluations revealed low levels of self-directed technical exploration and fragmented group collaboration when technical faults occurred. These operational deficiencies manifest across cognitive domain mastery (architectural concept comprehension), psychomotor performance (applied circuit design and code deployment), and affective engagement (persistence and collaborative problem-solving).

To address these multi-dimensional learning deficits, educational researchers have increasingly championed Project-Based Learning (PjBL) as a transformational instructional model in engineering education (Kokotsaki et al., 2016; Rodriguez-Sanchez et al., 2024). Grounded in experiential learning theory, PjBL positions authentic engineering challenges as the central driver of learning, requiring students to plan, execute, debug, and evaluate functional hardware-software prototypes (Abas, 2026; Sukackė et al., 2022). However, emerging literature underscores that adopting PjBL syntax—spanning problem identification, system design, iterative execution, and project defense—does not automatically guarantee superior learning outcomes (Guo et al., 2020). The pedagogical efficacy of PjBL is fundamentally mediated by students' subjective evaluative perception of how project syntax is structured, supported, and facilitated (Jalinus et al., 2019; Shin et al., 2021). If students perceive project requirements as ill-defined or lacking adequate instructional scaffolding, they experience overwhelming cognitive load, leading to frustration and disengagement.

Simultaneously, internal psychological attributes, most notably learning motivation, play a critical role in mediating academic achievement in technical disciplines (Ryan & Deci, 2020). According to Self-Determination Theory (SDT), intrinsic motivation and self-regulated goal orientation foster the psychological resilience required to persist through complex engineering troubleshooting by Bandura (Deng & Chen, 2025). In IoT coursework, where hardware component failures and code execution errors are standard occurrences, highly motivated students are more likely to exercise self-regulation, consult technical documentation independently, and sustain problem-solving effort (Bonnette & Miles, 2025).

While prior educational research has extensively evaluated motivation and PjBL independently across general science curricula (Beier et al., 2019; Schneider et al., 2022;

Spires et al., 2022; Stokes & Harmer, 2018; Wijnia et al., 2024), a critical research gap persists regarding their joint operational dynamics within specialized, highly technical engineering domains such as IoT. Existing studies predominantly rely on generic pedagogical survey frameworks that fail to account for how PjBL instructional syntax interacts with motivational resilience under conditions of technical debugging anxiety and cognitive overload (Gu et al., 2025; Nurasman et al., 2026; Ratu et al., 2025; Wijnia et al., 2024). Addressing this gap, this study investigates the partial and simultaneous influence of learning motivation and student perception of PjBL implementation on holistic learning outcomes in an undergraduate IoT engineering course. By synthesizing Cognitive Load Theory (CLT) and Self-Determination Theory (SDT), this paper provides a robust theoretical framework for optimizing technical curriculum design.

2. METHOD

This study utilized a quantitative causal-associative survey design to model the structural relationships among internal motivation, instructional perception, and academic performance (Cresswell & Guetterman, 2019). The research was conducted over a three-month period (March to May 2026) within the Department of Electronics Engineering and Information Technology, Faculty of Engineering, Universitas Negeri Makassar. The population comprised all 48 undergraduate students enrolled in the S1 Electronics Engineering Education program (2022 cohort, distributed across two academic classes) who had completed the mandatory IoT course. A saturated (total census) sampling method was applied, incorporating all 48 students as study participants.

Given the modest sample size inherent in specialized engineering cohorts, a post-hoc statistical power analysis was conducted using G*Power software (version 3.1.9.7) to evaluate sample adequacy and safeguard against Type II errors. For a multiple linear regression model with two predictor variables, a sample size of $N = 48$ achieved a statistical power ($1 - \beta$) of 0.812 at an alpha level of $\alpha = .05$ for a moderate population effect size ($f^2 = 0.25$). This confirms that the saturated sample provides sufficient statistical power to detect significant regression relationships without risking false-negative conclusions.

Three primary variables were operationalized in this research: two independent predictors—Learning Motivation (X_1) and Perception of PjBL Implementation (X_2)—and one dependent variable, Learning Outcomes (Y). Learning Motivation (X_1) was operationalized based on Pintrich's Motivated Strategies for Learning Questionnaire (MSLQ) framework, encompassing four dimensions: self-regulation, goal orientation, task value, and persistence during technical troubleshooting. Perception of PjBL Implementation (X_2) was operationalized around Shin et al. (2021) PjBL framework, evaluating design clarity, collaborative project structure, facilitator scaffolding quality, and perceived industry relevance. Both predictors were measured using a validated 26-item instrument scored on a 4-point Likert scale (1 = Strongly Disagree to 4 = Strongly Agree).

Learning Outcomes (Y) were operationalized as a composite score representing holistic mastery across cognitive, psychomotor, and affective domains. Unlike studies relying solely on theoretical written examinations, Y was calculated from standardized course assessment rubrics comprising three weighted components: (a) End-of-semester cognitive examination evaluating network protocol and system architecture comprehension (30%); (b) Objective psychomotor project portfolio rubric assessing circuit schematic accuracy, PCB wiring, micro-Python sensor script execution, and cloud telemetry functionality (50%); and (c) Structured affective observation rubric measuring teamwork, technical communication, and project defense (20%). Instrument content validity for Y was confirmed by a panel of three senior electronics engineering faculty members. The questionnaire instrument grid mapping indicators to item distributions is detailed in Table 1.

Table 1. The Questionnaire for Instrument Grid Mapping Indicators

Variable	Aspect / Dimension	Core Operational Indicators	Item Range
Learning Motivation (X_1)	Self-Regulation & Diligence	Focus maintenance & perseverance during hardware debugging	1, 2, 3, 4
	Goal Orientation & Value	Internal drive for competency mastery & perceived career alignment	5, 6, 7
	Environmental Responsiveness	Constructive utilization of instructor feedback & peer support	8, 9, 10
	Self-Reliance & Exploration	Independent troubleshooting & autonomous technical inquiry	11, 12, 13
Perception of PjBL (X_2)	Design & Syntax Clarity	Comprehension of project milestones, rubrics & IoT objectives	1, 2, 3, 4
	Collaborative Engagement	Peer participation, division of labor & technical communication	5, 6, 7
	Instructor Scaffolding	Timely technical assistance, facilitation & scaffolding quality	8, 9, 10
	Industry Relevance	Perceived alignment with professional IoT work-readiness skills	11, 12, 13

Note: All 26 items were measured on a 4-point favorable Likert scale.

Statistical procedures were executed using IBM SPSS Statistics version 27. Prior to parametric modeling, data quality was evaluated via Pearson product-moment correlation for construct validity and Cronbach's Alpha (standard threshold $\alpha \geq .70$ for robust research) for internal consistency reliability. Classical assumption tests were conducted, including Kolmogorov-Smirnov test for residual normality, deviation-from-linearity ANOVA for linearity, Variance Inflation Factor (VIF) for multicollinearity, and Glejser regression test for heteroscedasticity.

To control for potential Common Method Bias (CMB) arising from self-reported questionnaire data, Harman's Single-Factor test was conducted (Podsakoff et al., 2003). Unrotated principal component factor analysis revealed that the first single factor accounted for 34.2% of total variance, which is well below the critical 50% threshold.

This confirms that common method variance does not contaminate the empirical findings.

3. RESULTS AND DISCUSSION

Results

Summary of Instrument Validity and Reliability

To evaluate the structural integrity and psychometric robustness of the research instrument, comprehensive construct validity and internal consistency reliability assessments were performed across all 26 survey items. Item validity was verified by determining the corrected item-total correlation coefficient (r) for each item against the critical empirical threshold ($r_{\text{table}(46)} = .284, \alpha = .05$). The empirical analysis revealed that all 13 items measuring learning motivation yielded corrected item-total correlation coefficients ranging from $.503$ to $.873$. Similarly, the 13 items designed to capture students' perception of Project-Based Learning (PjBL) implementation demonstrated strong item discrimination power, with correlation values spanning from $.512$ to $.845$. Because all computed correlation coefficients substantially exceeded the critical value, every item was retained as a valid empirical indicator for subsequent data analysis.

Complementing the validity testing, the internal consistency of the measurement constructs was evaluated using Cronbach's alpha coefficient (α). The analysis yielded an exceptional reliability coefficient of $\alpha = .913$ for the learning motivation scale and $\alpha = .889$ for the perception of PjBL implementation scale. Both values significantly surpassed the widely accepted benchmark threshold of $.70$, indicating negligible measurement error and high stability across items. Collectively, these psychometric indices confirm that the 26-item instrument exhibits superior construct validity and rigorous internal consistency, thereby providing a highly trustworthy foundation for testing the research hypotheses and drawing generalizable empirical inferences.

Table 2. Summary of Instrument Validity and Reliability

Variable	**Number of Items**	**Corrected Item-Total Correlation (r)**	**Critical Value (r table, α=.05)**	**Validity Status**	**Cronbach's Alpha (α)**	**Reliability Evaluation**
Learning Motivation (X1)	13	.503 – .873	284	Valid	913	Excellent
Perception of PjBL Implementation (X2)	13	.512 – .845	284	Valid	889	High

Note: $N = 48$. *Critical* r*-table value is based on degrees of freedom* $df = N - 2 = 46$ *at a two-tailed significance level of* $\alpha = .05$. *Standard reliability threshold criterion: Cronbach's Alpha* $\alpha \geq .70$.

Classical Assumption Verification

Prior to conducting hypothesis testing via multiple linear regression analysis, all requisite parametric distributional assumptions were rigorously evaluated to prevent specification bias and ensure valid statistical inference. First, the evaluation of residual normality confirmed that the unstandardized residuals closely approximated a normal distribution, yielding an Asymptotic Significance of $p = .200$ and a Monte Carlo significance of $p = 1.000$, both substantially exceeding the standard $\alpha = .05$ alpha threshold. Second, assessment of bivariate structural relationships through analysis of variance (ANOVA) for deviation from linearity confirmed linear functional relationships between the dependent construct and both predictors. Specifically, non-significant deviations from linearity were established for both learning motivation, $F(13,33) = 1.302, p = .261$, and perception of Project-Based Learning (PjBL) implementation, $F(13,33) = 1.880, p = .071$.

Furthermore, collinearity diagnostics and variance stability assessments verified that the regression architecture satisfied all conditions of non-multicollinearity and homoscedasticity. Inter-predictor collinearity evaluation demonstrated identical Tolerance statistics of 0.995 (well above the critical $.10$ cutoff) and Variance Inflation Factor (VIF) values of 1.005 (substantially lower than the conservative 10.0 threshold), confirming the complete absence of inflated standard errors attributable to multicollinearity. Finally, Glejser heteroscedasticity regressive testing performed on absolute residuals produced significance values of $p = 1.000$ across both independent predictors. This indicates constant residual variance across all predicted values, thereby establishing homoscedasticity. Collectively, these rigorous diagnostic findings confirm that the empirical data fully satisfy all foundational assumptions required for robust linear regression modeling.

Table 3. Summary of Parametric Regression Diagnostic Tests

Assumption Test	Target / Predictor Construct	Statistical Test / Metric	Empirical Statistic / Value	Significance (p-value)	Diagnostic Conclusion
Normality	Regression Residuals	Kolmogorov-Smirnov (Asymp. Sig.) Monte Carlo Sig.	p=.200p=1.000	2,001,000	Normally Distributed
Linearity	Learning Motivation (X1)	Deviation from Linearity F (13,33)	F=1.302	261	Linear
	Perception of PjBL (X2)	Deviation from Linearity F (13,33)	F=1.880	71	Linear
Multicollinearity	Learning Motivation (X1)	Tolerance / VIF	Tolerance= 0.995VIF= 1.005	—	No Multicollinearity
	Perception of PjBL (X2)	Tolerance / VIF	Tolerance= 0.995VIF= 1.005	—	No Multicollinearity
Homoscedasticity	Learning Motivation (X1)	Glejser Test (Absolute Residuals)	t-statistic	1,000	Homoscedastic
	Perception of PjBL (X2)	Glejser Test (Absolute Residuals)	t-statistic	1,000	Homoscedastic

Multiple Linear Regression and Inferential Hypothesis Testing

Multiple linear regression analysis was conducted to evaluate partial and simultaneous predictor effects on IoT learning outcomes. Statistical parameters are summarized in Table 4.

Table 4. Multiple Linear Regression and Inferential Hypothesis Testing

Model Predictors	B	Std. Error	Beta (β)	t-statistic	p-value	95% CI for B
(Constant)	2.171	0.534	–	4.068	< .001	[1.095, 3.247]
Motivation (X_1)	0.021	0.009	.308	2.308	.026	[0.003, 0.039]
Perception PjBL (X_2)	0.020	0.009	.304	2.272	.028	[0.002, 0.038]

Model Diagnostics: R = .448, R² = .201, Adjusted R² = .165, F (2, 45) = 5.644, p = .007. Dependent Variable: Composite IoT Learning Outcomes (Y).

The empirical parameters of the linear regression model were evaluated to determine the individual and simultaneous structural contributions of the independent constructs toward student learning outcomes in the Internet of Things (IoT) coursework. As detailed in Table 3, the unstandardized linear regression model was formulated as $\hat{Y} = 2.171 + 0.021X_1 + 0.020X_2 + \varepsilon$. The baseline intercept constant of $\beta_0 = 2.171$ reflects the baseline magnitude of IoT learning outcomes when both explanatory variables are held at zero. To ascertain the relative predictive strength of each construct, standardized regression coefficients were evaluated. The standardized Beta coefficients revealed that learning motivation exerted a slightly larger relative partial influence ($\beta = .308$) on learning outcomes than students' perception of Project-Based Learning (PjBL) implementation ($\beta = .304$).

Partial hypothesis testing was subsequently executed to evaluate the direct effects of each independent variable. Partial Hypothesis 1 (H_1), which posited a statistically significant positive effect of learning motivation (X_1) on IoT learning outcomes (Y), was empirically supported, yielding $t(45) = 2.308, p = .026$ (where $p < .05$). This indicates that higher levels of intrinsic and extrinsic academic motivation significantly enhance student academic performance in IoT coursework. Similarly, Partial Hypothesis 2 (H_2), which hypothesized a positive structural impact of PjBL implementation perception (X_2) on IoT learning outcomes, was supported, $t(45) = 2.272, p = .028$ (where $p < .05$). These partial t-test statistics confirm that both student motivation and pedagogical syntax perception independently serve as statistically significant positive drivers of IoT academic achievement.

Finally, the simultaneous predictive capability of the joint regression model was evaluated through Analysis of Variance (ANOVA). Supporting Simultaneous Hypothesis 3 (H_3), the global omnibus test demonstrated a statistically significant overall model fit, $F(2,45) = 5.644, p = .007$ (where $p < .01$). The coefficient of determination reached $R^2 = .201$, indicating that the combined interaction of learning motivation and PjBL implementation accounts for 20.1% of the total variance observed in student IoT learning outcomes. After adjusting for potential sample-size inflation bias, the adjusted coefficient of determination (Adjusted $R^2 = .165$) reflects the true population variance explained by the specified model parameters, with the remaining 79.9% of variance attributable to exogenous instructional or affective factors outside the current model boundary.

Discussion

Motivational Resilience under Cognitive Load in IoT Debugging

The empirical validation of H1 (β = .308, p = .026) confirms that internal learning motivation is a vital determinant of academic achievement in IoT engineering coursework. This finding aligns with established self-regulated learning principles (Lejia et al., 2024; Ryan & Deci, 2020), while extending their applicability to complex technical domains. IoT coursework imposes unique cognitive demands: students must simultaneously synthesize digital electronics, embedded programming, and network infrastructure.

When analyzed through Cognitive Load Theory (Sweller, 2023), IoT laboratory tasks generate intense intrinsic and extraneous cognitive load during hardware-software debugging—such as troubleshooting unhandled socket exceptions or sensor signal noise. Under such conditions, learning motivation functions as an affective resilience buffer. Students exhibiting high intrinsic motivation and goal orientation display persistent self-regulation, treating technical faults as learning opportunities rather than insurmountable obstacles. Conversely, unmotivated students experience rapid cognitive overload and affective withdrawal when encountering hardware errors. This psycho-pedagogical dynamic explains why motivation directly dictates the quality of psychomotor portfolio execution and cognitive conceptual mastery.

Instructional Scaffolding and PjBL Syntax Execution

The confirmation of H2 (β = .304, p = .028) demonstrates that students' evaluative perception of PjBL syntax directly drives competency acquisition. This finding reinforces claims by Sánchez-García and Reyes-de-Cózar (2025) regarding the central role of instructional clarity in project-based environments. In an IoT context, effective PjBL execution requires explicit project milestones, clear performance rubrics, and structured facilitator scaffolding (Kokotsaki et al., 2016).

When students perceive PjBL syntax as coherent and aligned with authentic engineering practices, their germane cognitive load is optimized (Sweller, 2020). Clear project structures eliminate ambiguity regarding hardware schematics and programming requirements, allowing students to focus working memory capacity directly on schema construction and problem-solving. Furthermore, responsive instructor scaffolding during circuit assembly provides critical micro-level support, preventing cognitive overload and enhancing students' confidence in executing complex IoT prototypes.

Psycho-Pedagogical Synergy and Unexplained Variance Analysis

The simultaneous statistical significance of the model (F (2, 45) = 5.644, p = .007, $R^2 = .201$) highlights the interactive synergy between internal psychological attributes and external instructional design. Motivation provides the internal drive required for sustained effort, while structured PjBL syntax provides the methodological framework that directs that drive toward productive learning behaviors. Neither construct operates effectively in isolation: highly motivated students working within ill-structured PjBL environments experience cognitive exhaustion, whereas well-structured PjBL syntax fails to achieve desired outcomes if students lack internal motivation.

Crucially, the empirical finding that 79.9% of learning outcome variance remains unexplained (Adjusted $R^2 = .165$) provides a meaningful insight into engineering education. In highly technical engineering disciplines, achievement is multi-determined. Exogenous factors not captured in this two-predictor model—such as students' prior programming proficiency (C++/Python fundamentals), mathematical background, laboratory equipment availability, computing hardware capabilities, and individual cognitive load capacity—exert substantial influence over final learning outcomes (Guo et al., 2020). Recognizing this multi-variate landscape prevents over-simplified instructional interventions and highlights the necessity of multi-dimensional educational support systems.

4. CONCLUSION

This study establishes that internal learning motivation and student perception of Project-Based Learning implementation operate as complementary psycho-pedagogical predictors of academic success in higher education Internet of Things coursework. Both predictors demonstrate statistically significant partial and simultaneous positive contributions to holistic learning outcomes across cognitive, psychomotor, and affective domains. Methodologically validated through post-hoc power analysis and common method bias testing, the findings confirm that combining motivational support with clear instructional syntax enhances student performance in complex engineering environments.

Theoretical implications highlight the necessity of integrating Self-Determination Theory and Cognitive Load Theory when designing technical curricula. Motivation serves as an affective resilience mechanism during technical debugging, while structured PjBL syntax optimizes germane cognitive load. Practical implications for engineering faculty and instructional designers include: (a) Structuring PjBL syntax into modular, scaffolded milestones with explicit debugging guidelines to reduce extraneous cognitive load; (b) Incorporating formative feedback mechanisms to sustain student motivation during hardware failures; and (c) Modernizing laboratory infrastructure to ensure reliable hardware-software prototyping environments.

Limitations of this study include the single-institution sample and cross-sectional survey design. Future research should expand the empirical framework by incorporating multi-institutional cohorts, longitudinal tracking, and additional structural predictors such as prior programming self-efficacy, cognitive load indices, and laboratory facility quality.

REFERENCES

Abas, P. E. (2026). Learning to Engineer: Integrating Robotics-Centred Project-Based Learning in Early Undergraduate Education. *Education Sciences*, *16*(1), 105. https://doi.org/10.3390/educsci16010105

Beier, M. E., Kim, M. H., Saterbak, A., Leautaud, V., Bishnoi, S., & Gilberto, J. M. (2019). The effect of authentic project-based learning on attitudes and career aspirations in STEM. *Journal of Research in Science Teaching*, *56*(1), 3-23. https://doi.org/10.1002/tea.21465

Bonnette, R. N., & Miles, M. L. (2025). Getting the picture: Developing intrinsic motivation to self-regulate engineering documentation practices in a high school drone design challenge. *Journal of Engineering Education*, *114*(3), e70019. https://doi.org/10.1002/jee.70019

Cresswell, J. W., & Guetterman, T. C. (2019). Educational Research Planning, Conducting, And Evaluating Quantitative and Ualitative Research. Michigan.

Deng, K., & Chen, X. (2025). Exploring the impact of AI-driven emotional resilience on academic persistence, motivation, cognitive flexibility, and autonomy in self-regulated learning: A self-determination theory perspective. *Learning and Motivation*, *92*, 102167. https://doi.org/10.1016/j.lmot.2025.102167

Du, B., Chai, Y., Huangfu, W., Zhou, R., & Ning, H. (2021). Undergraduate university education in internet of things engineering in china: A survey. *Education Sciences*, *11*(5), 202. https://doi.org/10.3390/educsci11050202

Gumina, S., Patten, K., & Gerdes, J. (2024). The evolution of IoT education within an IT curriculum. *Education and Information Technologies*, *29*(6), 6723-6752. https://doi.org/10.1007/s10639-023-12088-7

Gu, P., Cheng, Z., Miaoting, C., Poggio, J., & Dong, Y. (2025). Integrating project-based learning with self-regulated learning to enhance programming learning motivation. *Journal of Computer Assisted Learning*, *41*(2), e70011. https://doi.org/10.1111/jcal.70011

Guo, P., Saab, N., Post, L. S., & Admiraal, W. (2020). A review of project-based learning in higher education: Student outcomes and measures. *International journal of educational research*, *102*, 101586. https://doi.org/10.1016/j.ijer.2020.101586

Hernandez-de-Menendez, M., Escobar Díaz, C. A., & Morales-Menendez, R. (2020). Engineering education for smart 4.0 technology: a review. *International Journal on Interactive Design and Manufacturing (IJIDeM)*, *14*(3), 789-803. https://doi.org/10.1007/s12008-020-00672-x

Jalinus, N., Syahril, S., & Nabawi, R. A. (2019). A comparison of the problem-solving skills of students in PjBL versus CPjBL model: An experimental study. *Journal of Technical Education and Training*, *11*(1). https://journal.uthm.edu.my/index.php/JTET/article/view/3154

Kokotsaki, D., Menzies, V., & Wiggins, A. (2016). Project-based learning: A review of the literature. *Improving schools*, *19*(3), 267-277. https://doi.org/10.1177/1365480216659733

Lejia, L. I. U., Hew, K. F., & Du, J. (2024). Design principles for supporting self-regulated learning in flipped classrooms: A systematic review. *International Journal of Educational Research*, *124*, 102319. https://doi.org/10.1016/j.ijer.2024.102319

Nurasman, M. S., Firmansyah, B., & Nasution, N. (2026). PjBL in Academic Writing Instruction in Higher Education: Challenges, Strategies, and Synthesis of Empirical Findings. *Bahtera: Jurnal Pendidikan Bahasa dan Sastra*, *25*(1), 51-61. https://doi.org/10.21009/bahtera.251.06

Pande, H., Patel, J., Patel, B., Patel, K., & Trivedi, H. (2026). Introduction to Internet of Things. In *Quantum Computing, Sensing and Communications for IoT* (pp. 35-77). Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-95-6276-3_2

Ratu, D. M., Nurhayati, N., Ratni, N. P., Nurmaisyah, N., Rantung, R., Kojongian, P. L., & Tatipang, D. P. (2025). Transforming Writing Education: An Investigation of Students' Experiences with Project-Based Learning in Teaching Writing: English. *Utamax: Journal of Ultimate Research and Trends in Education*, *7*(1), 44-57. https://doi.org/10.31849/utamax.v7i1.25037

Rodriguez-Sanchez, C., Orellana, R., Fernandez Barbosa, P. R., Borromeo, S., & Vaquero, J. (2024). Insights 4.0: Transformative learning in industrial engineering through problem-based learning and project-based learning. *Computer Applications in Engineering Education*, *32*(4), e22736. https://doi.org/10.1002/cae.22736

Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemporary educational psychology*, *61*, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860

Sánchez-García, R., & Reyes-de-Cózar, S. (2025). Enhancing project-based learning: A framework for optimizing structural design and implementation—A systematic review with a sustainable focus. *Sustainability*, *17*(11), 4978. https://doi.org/10.3390/su17114978

Schneider, B., Krajcik, J., Lavonen, J., Salmela-Aro, K., Klager, C., Bradford, L., ... & Bartz, K. (2022). Improving science achievement—Is it possible? Evaluating the efficacy of a high school chemistry and physics project-based learning intervention. *Educational Researcher*, *51*(2), 109-121. https://doi.org/10.3102/0013189X211067742

Shin, N., Bowers, J., Krajcik, J., & Damelin, D. (2021). Promoting computational thinking through project-based learning. *Disciplinary and Interdisciplinary Science Education Research*, *3*(1), 7. https://doi.org/10.1186/s43031-021-00033-y

Spires, H. A., Himes, M. P., & Krupa, E. (2022). Supporting students' science content knowledge and motivation through project-based inquiry (PBI) global in a cross-school collaboration. *Education Sciences*, *12*(6), 412. https://doi.org/10.3390/educsci12060412

Stadnicka, D., Sęp, J., Amadio, R., Mazzei, D., Tyrovolas, M., Stylios, C., ... & Navarro, J. (2022). Industrial needs in the fields of artificial intelligence, internet of things and edge computing. *Sensors*, *22*(12), 4501. https://doi.org/10.3390/s22124501

Stokes, A., & Harmer, N. (2018). The value of 'having a go': Trialing a project-based learning activity to inform curriculum design. *Journal of Geoscience Education*, *66*(4), 278-292. https://doi.org/10.1080/10899995.2018.1509599

Sukackė, V., Guerra, A. O. P. D. C., Ellinger, D., Carlos, V., Petronienė, S., Gaižiūnienė, L., ... & Brose, A. (2022). Towards active evidence-based learning in engineering education: A systematic literature review of PBL, PjBL, and CBL. *Sustainability*, *14*(21), 13955. https://doi.org/10.3390/su142113955

Sweller, J. (2020). Cognitive load theory and educational technology: J. Sweller. *Educational technology research and development*, *68*(1), 1-16. https://doi.org/10.1007/s11423-019-09701-3

Sweller, J. (2023). Discussion of the special issue on cognitive load theory. *British Journal of Educational Psychology*, *93*, 402-410. https://doi.org/10.1111/bjep.12606

Wijnia, L., Noordzij, G., Arends, L. R., Rikers, R. M., & Loyens, S. M. (2024). The effects of problem-based, project-based, and case-based learning on students' motivation: A meta-analysis. *Educational Psychology Review*, *36*(1), 29. https://doi.org/10.1007/s10648-024-09864-3

Winkens, A. K., Lemke, C., & Leicht-Scholten, C. (2024). How to teach resilience thinking in engineering education. *Sustainable and Resilient Infrastructure*, *9*(5), 513-530. https://doi.org/10.1080/23789689.2024.2356492

Wint, N., & Direito, I. (2026). How do engineering students understand and conceptualize individual resilience?. *Journal of Engineering Education*, *115*(1), e70047. https://doi.org/10.1002/jee.70047