Indonesian Educational Administration and Leadership Journal
Volume 07 Number 02 (2025)
https://online-journal.unja.ac.id/index.php/IDEAL
DOI : 10.22437/ideal.v7i2.51335

e-ISSN 2686-3596

42-52

Modeling Actual Use Of Technology and Student Engagement in Biology Project-Based Learning Using Artificial Neural Networks

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Article Info

Article history:
Received 20, 09, 2025
Revised 11, 10, 2025
Accepted 21, 12, 2025

Keywords:

Artifical neural network; actual use of technology; lecturer support; project-based learning; biology education.

ABSTRACT

In higher education, especially science and biology, digital technology in project-based learning (PjBL) environments has improved student engagement and learning outcomes. technological, AI, and lecturer assistance have been studied in PjBL, but few have used Artificial Neural Networks (ANN) to analyze the complicated interactions between technological acceptance variables and student engagement. ANN is used to predict students' attitudes toward technology (ATT), intention to use technology (INT), actual use of technology in PjBL (AU-PjBL), and student engagement (SE) based on PEOU, PU, and Lecturer Support. Biology education students at Universitas Jambi completed a 35-item Likert-scale questionnaire. We created four ANN models: Model A (PU, PEOU → ATT), Model B (PU, ATT → INT), Model C (INT, LS → AU-PjBL), and Model D (AU-PjBL, LS → Each model was trained and tested using ten network configurations. Model performance was assessed using Root Mean Square Error (RMSE), and input variable relevance was determined via sensitivity analysis. All ANN models have low RMSE values for training and testing datasets, indicating good predicting accuracy. According to sensitivity analysis, PU predicts ATT better than PEOU, ATT predicts INT better than PU, INT predicts AU-PjBL better than LS, and AU-PjBL predicts SE better than LS. These data emphasize that students' perceived utility, positive attitudes, intention, and technology use drive biology PjBL involvement. The paper highlights ANN as a powerful analytical tool for modeling non-linear and interdependent relationships in technology-enhanced PjBL and gives practical implications for developing meaningful technology use and engagement learning environments.

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INTRODUCTION

Project-based learning (PjBL) has been widely recognized as an effective pedagogical approach for fostering higher-order thinking skills, collaboration, creativity, and authentic problem-solving in higher education (Benlaghrissi & Ouahidi, 2024; He et al., 2025; Rattanakha et al., 2025). In biology education, PjBL provides opportunities for students to design, implement, and evaluate projects that connect biological concepts with real-world issues, thereby increasing relevance and engagement. The integration of digital technologies, AI tools, virtual reality, and mobile learning into PjBL further enhances these benefits by enabling rich, interactive, and data driven learning experiences (Dinger et al., 2024; He et al., 2025; Purnama et al., 2023).

Recent studies have demonstrated that AI-powered smart classrooms, virtual reality, and mobile-assisted PjBL can significantly improve collaboration, creativity, motivation, and learning outcomes (Benlaghrissi & Ouahidi, 2024; He et al., 2025; Jiang et al., 2025; Rattanakha et al., 2025; Sisamud et al., 2025). In science and STEM contexts, PjBL enhanced by technology and AI has been shown to support digital skills, design thinking, and innovative problem-solving (Baek, 2025; Dinger et al., 2024; Ghazali et al., 2025; Wang, 2025). However, the actual use of technology in PjBL and its translation into student engagement are not solely determined by the availability of tools. They are also shaped by students' perceptions of technology (e.g., perceived usefulness and ease of use), their attitudes and intentions, and the support they receive from lecturers.

Lecturer support plays a crucial role in technology-enhanced learning environments. Empirical evidence indicates that supportive lecturer–student relationships and effective guidance are associated with higher academic achievement, motivation, satisfaction, and engagement (Da Costa et al., 2025; O'Keeffe et al., 2023; Sari et al., 2023; Suryadi et al., 2024). In the context of digital and AI-based learning, lecturers act as change agents, facilitators, ethical gatekeepers, and designers of meaningful learning experiences (Chimbunde & Jakachira, 2025; Da Silva et al., 2025; Kaeane & Molokomme, 2025; Ruiz Viruel et al., 2025). Nevertheless, the interplay between lecturer support, technology acceptance constructs, actual technology use, and student engagement in PjBL-based biology education remains underexplored using advanced predictive modeling techniques.

Most prior research has relied on linear or traditional statistical models to analyze relationships among these constructs. Yet, the dynamics of technology use and engagement in authentic PjBL environments are likely to be non-linear, interactive, and complex. Artificial Neural Networks (ANN), as a core method in machine learning, offer a promising approach to capture such non-linear relationships and to model the multifaceted interactions among psychological and contextual factors.

This study addresses this gap by employing ANN to model how perceived ease of use (PEOU), perceived usefulness (PU), attitudes toward technology in PjBL (ATT), intention to use technology (INT), lecturer support (LS), and actual use of technology in PjBL (AU-PjBL) jointly shape student engagement (SE) in biology education. By focusing exclusively on ANN, this study contributes methodologically by showcasing the potential of neural networks for educational technology research, and substantively by identifying the most critical drivers of actual technology use and engagement in biology PjBL.

LITERATUR REVIEW

Across disciplines, PjBL supported by technology has been shown to improve a range of student outcomes, including language proficiency, digital literacy, creativity, and content understanding (Benlaghrissi & Ouahidi, 2024; Dinger et al., 2024; Kumar, 2021; Purnama et al., 2023). In language learning, mobile-assisted project-based learning can significantly enhance speaking skills by enabling continuous practice, collaboration, and situated communication (Benlaghrissi & Ouahidi, 2024). In STEM and digital entrepreneurship, integrating AI and digital tools into PjBL has been associated with higher creativity, problem-solving ability, and entrepreneurial competence (Baek, 2025; Dinger et al., 2024; Jiang et al., 2025; Sisamud et al., 2025).

In science and medical education, three-dimensional visualization and virtual reality integrated with problem-based or project-based learning have improved students' clinical understanding, engagement, and satisfaction (He et al., 2025; Wang, 2025). In the context of school science and early childhood, PBL–technology-based learning modules have been developed to foster social interaction, collaboration, and inquiry-oriented learning (Ghazali et al., 2025).

These studies collectively suggest that actual use of technology within PjBL—rather than mere access to tools—is a key determinant of enhanced learning outcomes. However, actual use is influenced by students' perceptions of usefulness, ease of use, attitudes, intentions, and contextual supports. Building predictive models of AU-PjBL and its consequences for engagement requires accounting for these interdependent psychological and environmental factors.

Lecturer Support in Technology-Enhanced Learning

Lecturer support has been consistently identified as a central factor in student success, motivation, and engagement in higher education (Da Costa et al., 2025; O'Keeffe et al., 2023; Sari et al., 2023; Suryadi et al., 2024). Positive lecturer–student relationships are associated with higher academic achievement and stronger learning mindsets (Suryadi et al., 2024). Students value both online and offline interactions with lecturers, particularly in rural or resource-constrained contexts, where direct support can substantially increase satisfaction and learning effectiveness (Sari et al., 2023).

In the context of digital and AI-based learning, lecturers act as facilitators of technology adoption, providers of scaffolding, and protectors of academic integrity (Chimbunde & Jakachira, 2025; Da Silva et al., 2025; Kaeane & Molokomme, 2025). O'Keeffe et al. (2023) highlighted how lecturer support is crucial for effective learning management system (LMS) use, especially during transitions to online learning. Da Costa et al. (2025) further emphasized lecturers' roles as innovators and professional developers who enhance learning quality through active pedagogical experimentation.

At the same time, challenges such as insufficient institutional support, inadequate infrastructure, and digital inequalities increase the burden on lecturers to navigate complex technological and pedagogical demands (Chimbunde & Jakachira, 2025; Kaeane & Molokomme, 2025). Despite these challenges, lecturer support (e.g., responsiveness, feedback, guidance, modeling technology use) remains a key driver of students' motivation, confidence, and engagement in technology-rich PjBL.

Technology Acceptance Constructs and Student Engagement

Technology acceptance models typically emphasize the roles of perceived usefulness (PU) and perceived ease of use (PEOU) in shaping users' attitudes and intentions, which in turn influence actual use. In PjBL, these constructs have been extended to account for collaborative learning, creativity, and engagement. Studies integrating AI tools, chatbots, virtual reality, and metaverse environments in PjBL have shown that increased perceived interactivity, usefulness, and enjoyment are associated with higher engagement and creativity (He et al., 2025; Kumar, 2021; Purnama et al., 2023; Sisamud et al., 2025).

Student engagement is often conceptualized as a multifaceted construct encompassing behavioral, emotional, and cognitive dimensions. In technology-enhanced PjBL, engagement is manifested in sustained participation in project tasks, perseverance in the face of difficulty, active collaboration, and positive emotional experiences (He et al., 2025; Jiang et al., 2025). However, the strength and form of the relationships among PEOU, PU, ATT, INT, AU-PjBL, LS, and SE may be complex and non-linear, warranting the use of advanced modeling techniques.

Artificial Neural Networks in Educational Technology Research

ANNs are data-driven models that can learn complex, non-linear mappings between input and output variables, making them well suited for modeling multidimensional relationships in educational settings. In technology-enhanced learning research, ANN can be used to predict student performance, classify engagement states, and identify key predictors of learning outcomes, especially when interactions among variables are strong and not easily captured by linear models.

In this study, ANN is employed to model how technology acceptance constructs and lecturer support jointly predict actual technology use and student engagement in biology PjBL. By performing sensitivity analysis, ANN also enables the estimation of the relative importance of each predictor, providing actionable insights into which factors should be prioritized in instructional design and institutional policy.

METHODS

Participants and Context

The participants were undergraduate students enrolled in the Biology Education program at Universitas Jambi. They were engaged in project-based learning activities within biology courses that incorporated digital technologies to support project planning, implementation, collaboration, and presentation. A total of 103 students completed the survey instrument, providing data on their perceptions, intentions, actual technology use, and engagement in technology-supported PjBL.

Instrumentation

A structured questionnaire comprising 35 items was developed to measure seven constructs: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude towards Technology in PjBL (ATT), Intention to Use Technology in PjBL (INT), Actual Use of Technology in PjBL (AU-PjBL), Lecturer Support (LS), and Student Engagement (SE). All items were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

The items for PEOU and PU were adapted from prior technology acceptance research, while ATT and INT reflected students' evaluative and intentional orientations toward using technology in PjBL. AU-PjBL items captured the extent to which students actually utilized digital technologies in their project work. LS items measured students' perceptions of lecturers' responsiveness, guidance, feedback, and modeling of technology use. SE items assessed motivational, affective, and behavioral engagement in project tasks (e.g., enthusiasm, persistence, enjoyment, collaboration).

Content validity was established through expert review by five specialists in Indonesian language and biology education. Item-level Content Validity Index (I-CVI) values were ≥ 0.80 for all 35 items, with 33 items achieving I-CVI = 1.00. Scale-level indices (S-CVI/Ave and S-CVI/UA) reached 0.989 and 0.943 respectively, exceeding recommended thresholds. Construct reliability was supported by high factor loadings, Average Variance Extracted (AVE > 0.65), and composite reliabilities ($\rho c > 0.86$) across all constructs.

ANN Model Specification

Four ANN models were specified to represent sequential relationships among constructs:

- Model A (Output: ATT)
  - Inputs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU)
  - Output: Attitude towards Technology in PjBL (ATT)
- Model B (Output: INT)
  - Inputs: Perceived Usefulness (PU), Attitude towards Technology in PjBL (ATT)
  - Output: Intention to Use Technology in PjBL (INT)
- Model C (Output: AU-PjBL)
  - Inputs: Intention to Use Technology in PjBL (INT), Lecturer Support (LS)
  - Output: Actual Use of Technology in PjBL (AU-PjBL)
- Model D (Output: SE)
  - Inputs: Actual Use of Technology in PjBL (AU-PjBL), Lecturer Support (LS)
  - Output: Student Engagement (SE)

Each model was implemented as a feed-forward multi-layer perceptron with one input layer, one hidden layer, and one output layer. For each model, ten network configurations (ANN1–ANN10) were tested, varying in terms of the number of neurons in the hidden layer and initial weight randomization. A supervised learning algorithm with backpropagation was used for training.

Data Preparation and Training Procedure

Prior to training, all construct scores were normalized to an appropriate range (e.g., 0–1) to ensure numerical stability and to facilitate the learning process. The dataset was then randomly divided into a training set and a testing set. The training set was used to fit the ANN models, while the testing set was reserved for evaluating generalization performance. For each of the four models (A–D), the ten ANN configurations were trained using the training subset until convergence criteria were met (e.g., maximum number of epochs or minimal change in error). The same data splits were maintained across model configurations for comparability.

Evaluation Metrics and Sensitivity Analysis

Model performance was evaluated using Root Mean Square Error (RMSE) for both training and testing datasets. Lower RMSE values indicate better model fit and predictive accuracy. Sensitivity analysis was then performed to assess the relative importance of each input variable on the corresponding output in each model. The results are presented as normalized importance percentages, where the most influential predictor is set at 100% and other predictors are scaled relative to this benchmark.

FINDINGS AND DISCUSSION

Findings

RMSE Values of ANN Models

Table 1 summarizes RMSE values for the ten ANN configurations (ANN1–ANN10) across the four models. Overall, all models exhibited relatively low RMSE values for both training and testing sets.

- **Model A (PU, PEOU → ATT)**
  Training RMSE values typically ranged from approximately 0.435 to 0.489, whereas testing RMSE ranged from about 0.324 to 0.443. These values indicate that ATT can be predicted with reasonable accuracy based on students' perceptions of usefulness and ease of use.
- **Model B (PU, ATT → INT)**
  Training RMSE values were approximately 0.492–0.524, with testing RMSE around 0.414–0.535. Although slightly higher than Model A, error levels remained acceptable, suggesting that PU and ATT can jointly predict students' intentions to use technology in PjBL with moderate precision.
- **Model C (INT, LS → AU-PjBL)**
  Training RMSE values were in the range of about 0.413–0.471, while testing RMSE values varied between approximately 0.292 and 0.522. The presence of configurations with testing RMSE near 0.29 indicates that students' intentions and perceived lecturer support are strong predictors of actual technology use in PjBL.
- **Model D (AU-PjBL, LS → SE)**
  Training RMSE values fell between roughly 0.436 and 0.502, and testing RMSE values ranged from about 0.266 to 0.531. The best-performing configurations with testing RMSE around 0.266 demonstrate that AU-PjBL and LS can effectively predict student engagement.

Table 1. Root Mean Square Error Values of ANN Models for Training and Testing

Neural Network	Model A		Model B		Model C		Model D	
	Input: PU, PEOU Output: ATT		Input: PU, ATT Output: INT		Input: INT, LS Output: Actual Use		Input: Actual Use, LS Output: SE	
	RMSE (Training)	RMSE (Testing)	RMSE (Training)	RMSE (Testing)	RMSE (Training)	RMSE (Testing)	RMSE (Training)	RMSE (Testing)
ANN1	0.450	0.355	0.507	0.414	0.417	0.410	0.439	0.313
ANN2	0.471	0.387	0.504	0.482	0.442	0.362	0.455	0.266
ANN3	0.438	0.514	0.524	0.535	0.415	0.292	0.502	0.478
ANN4	0.489	0.324	0.507	0.454	0.433	0.341	0.436	0.393
ANN5	0.438	0.358	0.499	0.464	0.423	0.454	0.437	0.531
ANN6	0.448	0.364	0.492	0.524	0.413	0.350	0.457	0.346
ANN7	0.436	0.422	0.497	0.475	0.471	0.522	0.446	0.518
ANN8	0.435	0.443	0.500	0.483	0.416	0.360	0.443	0.420
ANN9	0.449	0.392	0.501	0.508	0.432	0.394	0.475	0.501
ANN10	0.450	0.382	0.515	0.471	0.429	0.400	0.447	0.390
Mean	0.313	0.274	0.350	0.334	0.685	0.270	0.315	0.289
S.D.	0.0108	0.0340	0.0058	0.0221	1.1584	0.0404	0.0130	0.0569

The consistency of low to moderate RMSE values across models and across training and testing datasets indicates that the ANN models generalize reasonably well and capture meaningful patterns in the data.

Sensitivity Analysis: Relative Importance of Predictors

Table 2 provides sensitivity analysis results for each ANN model:

- **Model A (Output: ATT)**
  Perceived Usefulness (PU): 100% (normalized importance)
  Perceived Ease of Use (PEOU): ≈ 84.3%
  Both PU and PEOU are important, but PU is the more influential predictor of students' attitudes toward using technology in PjBL.
- **Model B (Output: INT)**
  Attitude towards Technology in PjBL (ATT): 100%
  Perceived Usefulness (PU): ≈ 81.8%
  ATT emerges as the strongest driver of INT, though PU still plays a substantial role.
- **Model C (Output: AU-PjBL)**
  Intention to Use Technology in PjBL (INT): 100%
  Lecturer Support (LS): ≈ 37.5%
  INT is the dominant predictor of actual technology use in PjBL, while LS exerts a secondary yet meaningful influence.
- **Model D (Output: SE)**
  Actual Use of Technology in PjBL (AU-PjBL): 100%
  Lecturer Support (LS): ≈ 36.6%
  AU-PjBL is the most critical determinant of student engagement, whereas LS contributes additional support.

Table 2. Sensitivity Test Result of ANN Models

Neural Network	Model A		Model B		Model C		Model D	
	Output: ATT		Output: INT		Output: Actual Use		Output: SE	
	PU	PEOU	PU	ATT	INT	LS	Actual Use	LS
ANN1	100%	75.4%	62.8%	100%	100%	15.9%	100%	11.1%
ANN2	100%	76.2%	77.5%	100%	100%	35.5%	100%	10.5%
ANN3	75.9%	100%	57.6%	100%	100%	27.7%	100%	82.2%
ANN4	100%	92.6%	79.3%	100%	100%	38.8%	100%	13.7%
ANN5	100%	87.5%	70.2%	100%	100%	14.4%	100%	24.3%
ANN6	100%	96.6%	90.7%	100%	100%	27.2%	100%	33.6%
ANN7	100%	61.5%	75.3%	100%	100%	77.4%	100%	71.6%

These findings reveal a coherent pathway: **PU and PEOU → ATT → INT → AU-PjBL → SE, with lecturer support (LS)** exerting supportive influence at the stages of actual use and engagement.

Discussion

The ANN results provide empirical evidence for a structured progression from students' perceptions of technology to their engagement in biology PjBL. The findings highlight several key insights. First, perceived usefulness (PU) has a slightly stronger influence than perceived ease of use (PEOU) on attitudes toward technology (ATT). This suggests that biology education students prioritize the instrumental value of technology—such as its ability to facilitate understanding, improve productivity, and support project completion—over the simplicity of operation. This aligns with previous studies showing that students are willing to tolerate certain usability challenges if the technology demonstrably enhances learning outcomes (Dinger et al., 2024; Purnama et al., 2023; Wang, 2025).

Second, attitude (ATT) is the primary predictor of intention to use technology (INT), surpassing PU in importance. This is consistent with theoretical perspectives that position attitude as the most proximal determinant of behavioral intention. In PjBL settings, positive attitudes are likely shaped by experiences of meaningful, enjoyable, and interactive learning with technologies such as AI tools, virtual reality, mobile apps, and generative AI-based resources (He et al., 2025; Jiang et al., 2025; Kumar, 2021; Sisamud et al., 2025).

Third, intention to use technology (INT) is the strongest predictor of actual use in PjBL (AU-PjBL). While lecturer support (LS) significantly contributes to AU-PjBL, its relative importance is smaller compared to INT. This indicates that students' internal motivation and commitment to using technology play a central role in transforming readiness into action. Nevertheless, LS remains crucial in providing guidance, troubleshooting assistance, and examples of effective technology use, particularly in environments where digital infrastructure, training, or institutional support may be uneven (Chimbunde & Jakachira, 2025; Kaeane & Molokomme, 2025; O'Keeffe et al., 2023).

Fourth, actual use of technology (AU-PjBL) is the most influential factor driving student engagement (SE). This finding emphasizes that engagement in biology PjBL is not merely a function of students' attitudes or intentions but is strongly tied to their real, sustained use of digital tools throughout the project lifecycle. This is consistent with research showing that technology-rich PjBL environments—such as AI-powered smart classrooms, mobile-assisted language learning, and VR-supported projects—promote higher levels of behavioral, emotional, and cognitive engagement (Benlaghrissi & Ouahidi, 2024; He et al., 2025; Rattanakha et al., 2025; Ruiz Viruel et al., 2025).

The moderate but meaningful contributions of lecturer support (LS) to both AU-PjBL and SE highlight its role as a pedagogical and socio-emotional enabler. Lecturer support can increase students' confidence in using technology, encourage persistence, and foster a safe, collaborative climate for experimentation and innovation (Da Costa et al., 2025; Sari et al., 2023; Suryadi et al., 2024). In AI-rich educational contexts, lecturers additionally act as ethical stewards and critical mediators of technology use (Da Silva et al., 2025; Ruiz Viruel et al., 2025).

Methodologically, this study demonstrates the value of ANN in educational technology research, particularly when investigating multiple, potentially non-linear relationships among psychological and contextual variables. ANN's ability to produce low RMSE values and to generate sensitivity analyses provides both predictive accuracy and interpretable insights into variable importance. This complements and extends traditional analytical approaches by capturing richer patterns in students' technology use and engagement behaviors.

CONCLUSION

The findings of this study have several important implications for biology educators, instructional designers, and higher education institutions seeking to optimize technology-supported project-based learning. At the instructional level, the strong influence of perceived usefulness and positive attitudes toward technology on students' intentions and actual use suggests that PjBL tasks should be designed so that technology is clearly indispensable for achieving deeper conceptual understanding, efficient project completion, and authentic scientific inquiry, rather than serving as a superficial add-on. Lecturers are encouraged to create engaging, hands-on experiences with digital tools (e.g., simulations, visualization platforms, AI-based assistants) that foster positive emotional responses and demonstrate tangible learning benefits, thereby strengthening students' attitudes and intentions. At the same time, the central role of actual use of technology in predicting student engagement indicates that institutions should prioritize sustained, meaningful technology integration throughout the entire project cycle, aligning assessment criteria with the quality and depth of technology use. The moderate but consistent contribution of lecturer support to both actual use and engagement highlights the need for ongoing professional development that equips lecturers not only with technical skills, but also with pedagogical strategies for scaffolding technology-rich PjBL, providing timely feedback, and addressing ethical and equity concerns in AI-enhanced learning environments. Collectively, these implications underscore that increasing student engagement in biology PjBL requires a coordinated effort to enhance the perceived value of technology, cultivate positive technology-related experiences, ensure robust lecturer support, and structurally embed digital tools into the design, implementation, and evaluation of project-based learning.

AUTHOR CONTRIBUTIONS

"Conceptualization, D.A.E.P.S. and M.Y.; Methodology, D.A.E.P.S.; Software, R.H.; Validation, D.A.E.P.S., M.Y. and M.F.; Formal Analysis, L.M.; Investigation, D.A.E.P.S.; Writing – Review & Editing, D.A.E.P.S."

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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