



Interactive Learning Technology in Teacher Training: Effects on Teacher Performance and Professional Competence

¹Sabariah*, Ruffi'i, ¹Adi Bandono, ²Supriyanto, ¹Muhammad Yasfini Nur, ¹Erika, ¹Amalia Khasanah Marzuki.

Corresponding Author: *sabariah@unipasby.ac.id

¹Universitas PGRI Adi Buana Surabaya, Surabaya, Indonesia

²Universitas Negeri Surabaya, Surabaya Indonesia

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ABSTRACT

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The increasing adoption of digital technologies in education has highlighted the need for effective teacher training to improve instructional quality and professional development. However, empirical evidence on the effectiveness of interactive learning technology in vocational teacher training remains limited. This study examines the influence of interactive learning technology on teacher performance and professional competence among teachers participating in training programs at the Technical Development and Vocational Skills Unit in East Java, Indonesia. A quantitative approach was employed using SEM-PLS with data collected from 156 teachers. The findings indicate that interactive learning technology positively enhances teacher performance, which subsequently contributes to the improvement of professional competence. Teachers' initial knowledge was identified as the strongest factor influencing both performance and competence. The study highlights the importance of integrating interactive digital technologies with teachers' prior knowledge to maximize the effectiveness of professional development programs. These findings contribute to the growing literature on technology-enhanced teacher development and provide practical implications for designing more effective vocational teacher training programs.

Keywords

Digital Pedagogy

Digital Literacy

Technology Acceptance

Vocational Education

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Introduction

The rapid advancement of digital technologies, artificial intelligence (AI), and online learning environments has fundamentally transformed educational practices and teacher professional development worldwide. In this digital era, teachers are expected not only to master subject knowledge but also to effectively integrate technology into pedagogical practices to create engaging, inclusive, and student-centered learning environments. Consequently, developing teachers' digital competence has become a strategic priority in educational reform across many countries [1].

Recent studies have emphasized that interactive learning technologies—including learning management systems, AI-supported instructional tools, virtual learning environments, and digital collaboration platforms—play an essential role in improving teacher knowledge, instructional quality, and professional growth. Rather than functioning solely as instructional tools, these technologies facilitate reflective practice, collaborative learning, and continuous professional development, thereby supporting teachers in adapting to rapidly changing educational demands [2], [3].

Teacher professional development has therefore shifted from conventional workshop-based activities toward technology-enhanced learning models that emphasize continuous, practice-oriented, and evidence-based learning. A recent systematic review by [4] concluded that technology-based professional learning programs generally improve teachers' instructional practices, although their effectiveness depends on teachers' prior knowledge, institutional support, and the quality of training design. Similarly, [5] reported that AI-supported professional development enhances teachers' Technological Pedagogical Content Knowledge (TPACK), digital competence, and instructional innovation when implemented through structured and sustainable learning experiences.

Within the Indonesian context, educational digital transformation has accelerated considerably following the implementation of national education reforms and post-pandemic digital learning initiatives. Programs such as the Professional Teacher Education Program (PPG) have strengthened teachers' technological and pedagogical competencies; however, improvements remain uneven across educational sectors, particularly within vocational education and technical training institutions. [6] demonstrated that participation in PPG significantly contributes to teachers' TPACK development, yet competency growth differs according to teachers' career stages and professional experience.

Although previous research consistently demonstrates the positive contribution of educational technology to teacher development, existing studies primarily examine improvements in digital competence, TPACK, or technology acceptance. Most investigations evaluate training outcomes descriptively or focus on general educational settings without

examining the underlying mechanisms through which interactive learning technology enhances teachers' professional competence. Furthermore, systematic reviews have highlighted the need for empirical studies employing comprehensive analytical models capable of explaining the relationships among technology utilization, teachers' prior knowledge, instructional performance, and professional competence within specific educational contexts [1], [7].

This limitation is particularly evident in vocational teacher training institutions, where teachers are required to integrate rapidly evolving industrial technologies into classroom practice. Unlike general education, vocational education requires teachers to simultaneously develop pedagogical expertise, technological proficiency, and industry-relevant competencies. Despite the increasing implementation of interactive learning technologies in vocational teacher training, empirical evidence regarding their direct and indirect effects on teacher performance and professional competence remains limited, especially in developing countries such as Indonesia. Moreover, few studies have examined these relationships using Structural Equation Modeling–Partial Least Squares (SEM-PLS), which enables simultaneous evaluation of complex causal relationships among latent constructs.

Accordingly, this study addresses three important research gaps. First, previous studies have largely investigated digital competence or TPACK independently, whereas limited research has integrated Interactive Learning Technology, Initial Knowledge, Teacher Performance, and Professional Competence into a unified structural model. Second, empirical evidence regarding the mediating role of teacher performance in explaining how interactive learning technology contributes to professional competence remains scarce, particularly in vocational teacher training contexts. Third, studies conducted within Indonesian Technical Development and Vocational Skills Units (UPT) remain very limited, despite these institutions playing a strategic role in preparing teachers for technology-driven vocational education.

Therefore, this study develops and empirically tests a structural model examining the direct and indirect relationships among interactive learning technology, initial knowledge, teacher performance, and professional competence using the SEM-PLS approach. By focusing on teachers participating in vocational training programs at the Technical Development and Vocational Skills Unit in East Java, Indonesia, this research contributes to the growing literature on technology-enhanced professional development while providing evidence-based recommendations for designing more effective and sustainable teacher training programs in the digital era.

Literature Review

Interactive learning technology has transformed teacher training from a content-delivery process into a more participatory, reflective, and practice-oriented learning

environment. Digital platforms can support collaboration, independent learning, feedback, and student-centered instructional design when technology is integrated with clear pedagogical objectives [2]. However, access to digital tools alone does not guarantee better teaching. Technology-focused professional development produces stronger outcomes when it combines technical knowledge, pedagogical practice, sustained assistance, and performance-based evaluation [1], [4].

The TPACK framework explains that effective technology integration requires teachers to combine technological, pedagogical, and content knowledge. Interactive digital content can improve cognitive achievement and instructional production skills when it is designed through an integrated TPACK approach [8]. Evidence from Indonesian teacher education also shows that professional preparation pathways influence teachers' TPACK development and their capacity to apply technology meaningfully in teaching [9].

Prior knowledge is equally important because teachers enter training with different levels of understanding, professional experience, digital familiarity, and learning readiness. Teachers with stronger prior knowledge can connect new material with existing cognitive structures and apply technological innovations more efficiently. Structured professional training can strengthen digital and pedagogical competence, but its effectiveness depends on participants' initial readiness and opportunities to practise new skills [3], [10].

Teacher performance reflects the practical application of knowledge and competence through lesson planning, instructional implementation, classroom management, learning assessment, and continuous professional development. Recent studies show that AI-based technologies can support teaching performance and instructional design when teachers retain critical control over technological outputs [11], [12], [13]. Nevertheless, professional competence remains multidimensional and requires careful measurement across pedagogical, professional, social, and personal domains [14].

Previous studies have largely examined digital competence, TPACK, technology adoption, or teaching performance separately. Limited research has tested an integrated model linking interactive learning technology, prior knowledge, teacher performance, and professional competence among in-service teachers. This study addresses that gap by examining whether technology and prior knowledge improve professional competence through strengthened teacher performance.

H1: Interactive learning technology has a positive effect on teacher performance.

H2: Prior knowledge has a positive effect on teacher performance.

H3: Teacher performance has a positive effect on professional competence.

Material and Methods

A. Research Design

This study employed a quantitative approach using an explanatory cross-sectional survey design. The explanatory design was selected because the study aimed to examine the causal relationships among learning technology, prior knowledge, teacher performance, and teacher competence. The data were analyzed using partial least squares structural equation modeling, hereafter referred to as PLS-SEM, with SmartPLS [version number]. PLS-SEM was considered appropriate because the proposed model included multiple latent constructs, reflective indicators, and several structural relationships that needed to be estimated simultaneously [15].

The structural model examined three principal relationships. These relationships included the effect of learning technology on teacher performance, the effect of prior knowledge on teacher performance, and the effect of teacher performance on teacher competence. The teacher constituted the unit of analysis. All constructs were measured at the individual level based on the respondents' knowledge, experiences, professional practices, and perceptions.

B. Population and Respondent Selection

The target population comprised teachers who participated in training programs organized by the Technical and Vocational Skills Development Unit, locally referred to as the Unit Pelaksana Teknis, or UPT. The research sample consisted of 156 teachers from various districts and municipalities across East Java Province, Indonesia.

Respondents were selected using purposive sampling because not all teachers in the broader population possessed the experience required to evaluate the constructs included in the proposed model. This sampling technique enabled the researchers to select participants whose professional backgrounds, training experiences, and use of learning technology were directly relevant to the objectives of the study.

The inclusion criteria required respondents to: (1) be active teachers at a formal educational institution; (2) have at least one year of teaching experience; (3) have participated in a training program organized by the Technical and Vocational Skills Development Unit; (4) be directly involved in lesson planning, instructional delivery, classroom management, and student learning assessment; (5) have used digital technology or digital learning media for at least one semester before the survey; (6) voluntarily agree to participate in the study; and (7) provide informed consent after receiving information about the research objectives and procedures.

The exclusion criteria covered educational personnel without direct teaching responsibilities, teachers who were inactive or on leave during the data collection period, participants who had no experience using learning technology within the specified period, and respondents who submitted substantially incomplete questionnaires. These criteria ensured that the selected respondents possessed sufficient professional experience to assess all constructs included in the research model.

Based on these criteria, 156 teachers were included in the final analysis. Because the study applied purposive sampling, the findings were not intended to provide statistical generalization to the entire teacher population in Indonesia. The external validity of the findings is therefore limited to teachers with professional and institutional characteristics comparable to those of the respondents in this study.

C. Research Instrument

Data were collected using a structured, closed-ended questionnaire consisting of two sections. The first section collected information on respondent characteristics, including gender, age, educational attainment, teaching experience, employment status, school level, area of origin, and experience in using learning technology. The second section measured the four latent constructs through 17 statement items.

The learning technology construct was measured using four items. Prior knowledge was measured using four items. Teacher performance was measured using five items, while teacher competence was measured using four items. Each indicator was represented by one questionnaire item.

All items were measured using a five-point Likert scale, ranging from 1 to 5, where 1 indicated strongly disagree, 2 indicated disagree, 3 indicated neutral, 4 indicated agree, and 5 indicated strongly agree. Higher scores indicated more favorable assessments of the respective constructs.

The learning technology indicators were developed by adapting the concepts of perceived ease of use and perceived usefulness proposed by [16], together with the UNESCO ICT Competency Framework for Teachers [17]. The indicators covered the ease of using learning technology, the availability of digital learning media and devices, the integration of technology into instructional activities, and the perceived effectiveness of technology in improving learning quality.

The prior knowledge indicators were adapted from the concepts of existing knowledge, previous learning experience, knowledge integration, and cognitive readiness developed by [18], [19]. In this study, prior knowledge referred specifically to the knowledge, experience, and cognitive readiness possessed by teachers before learning or applying new instructional materials and practices.

Teacher performance indicators were developed based on the professional responsibilities of teachers in planning instruction, delivering instruction, managing classrooms, evaluating student learning, and engaging in continuous professional development. The indicators were informed by Law of the Republic of Indonesia No. 14 of 2005 concerning Teachers and Lecturers and the empirical work of [20].

Teacher competence was operationalized through four dimensions, namely pedagogical competence, professional competence, social competence, and personal competence. These dimensions were derived from Law of the Republic of Indonesia No. 14 of 2005 and Regulation of the Minister of National Education of the Republic of Indonesia No. 16 of 2007 concerning Academic Qualification Standards and Teacher Competencies.

The questionnaire items were adapted to the professional and institutional context of teachers participating in training at the Technical and Vocational Skills Development Unit. Linguistic adjustments were made to improve clarity and contextual relevance without altering the conceptual domain of each construct.

Table 1. Operationalization of Variables

Variable	Indicators	Brief definition
Learning Technology (X1)	X1.1 Ease of using learning technology; X1.2 Availability of digital learning media and devices; X1.3 Utilization of technology in learning; X1.4 Effectiveness of technology in improving learning quality	Teachers' perceptions of the accessibility, use, and instructional value of digital technology.
Prior Knowledge (X2)	X2.1 Initial understanding of learning materials; X2.2 Previous experience related to the material; X2.3 Ability to connect prior knowledge with new material; X2.4 Learning readiness based on existing knowledge	Teachers' existing knowledge, experience, and cognitive readiness before learning new material.
Teacher Performance (Y1)	Y1.1 Lesson planning; Y1.2 Instructional delivery; Y1.3 Classroom management; Y1.4 Evaluation of learning outcomes; Y1.5 Continuous professional development	Teachers' effectiveness in carrying out instructional and professional responsibilities.
Teacher Competence (Y2)	Y2.1 Pedagogical competence; Y2.2 Professional competence; Y2.3 Social competence; Y2.4 Personal competence	Teachers' integrated capacity to perform professional duties effectively.

D. Data Collection Procedure

Data were collected during training activities organized by the Technical and Vocational Skills Development Unit in East Java Province, Indonesia. Research permission was obtained from the responsible institution. The questionnaire was distributed through paper-based, online, or combined methods and completed independently by the respondents. Participation was voluntary, and no direct personal identifiers were collected. Questionnaires with substantial missing data, implausible response patterns, or respondents who did not meet the inclusion criteria were excluded. After screening, 156 valid questionnaires were retained for the PLS-SEM analysis.

Prospective respondents received an information sheet explaining the research objectives, survey procedures, voluntary nature of participation, confidentiality safeguards, and their right to discontinue participation without penalty. The respondents were informed that their decision to participate or refuse participation would not affect their employment, training status, professional assessment, or institutional relationship with the training provider.

The questionnaire was administered, Respondents completed the questionnaire independently. The instrument did not request names or other direct personal identifiers. The data screening process excluded questionnaires with substantial missing responses, implausible response patterns, or evidence that the respondent did not meet the inclusion criteria.

A total of [number distributed] questionnaires were distributed, of which [number returned] were returned. After data screening, 156 complete and eligible questionnaires were retained for the final PLS-SEM analysis.

E. Ethical Considerations

Before completing the questionnaire, each respondent received information concerning the objectives, procedures, expected benefits, potential risks, data management arrangements, and participant rights. Written or electronic informed consent was obtained from every participant. Respondents were free to decline participation or withdraw from the study without any adverse consequences. The collected data were stored securely and were accessible only to the research team. The results were reported in aggregate form to prevent the identification of individual respondents or their employing institutions.

F. Data Analysis Using PLS-SEM

Data analysis was conducted in two stages. The first stage evaluated the measurement model, while the second assessed the structural model. Because the constructs were specified reflectively, the measurement model assessment covered indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

Indicator reliability was assessed using outer loadings. Indicator loadings of 0.708 or higher were considered satisfactory because they indicated that the construct explained at least 50 percent of the indicator variance. Indicators with loadings between 0.40 and 0.70 were considered for removal only when their exclusion improved composite reliability or average variance extracted without compromising the construct's conceptual coverage [21].

Internal consistency reliability was evaluated using Cronbach's alpha, rho_A, and composite reliability. Values between 0.70 and 0.95 were considered acceptable. Values above 0.95 were examined critically because they could indicate item redundancy rather than superior measurement quality.

Convergent validity was assessed using the average variance extracted, or AVE. An AVE value above 0.50 indicated that a construct explained more than half of the variance in its indicators. Discriminant validity was assessed using the heterotrait-monotrait ratio of correlations, or HTMT. HTMT values below 0.85 indicated adequate discriminant validity for conceptually distinct constructs, while values below 0.90 were considered acceptable for constructs with greater conceptual similarity.

The structural model assessment began with an examination of lateral collinearity using the variance inflation factor, or VIF. VIF values below 3 were considered preferable, although values below 5 were still regarded as acceptable in less restrictive assessments. The structural relationships were then evaluated using standardized path coefficients, t-values, p-values, and confidence intervals.

The explanatory power of the model was assessed using the coefficient of determination, or R^2 , for the endogenous constructs. The effect of each exogenous construct was examined using the f^2 effect size. Predictive relevance was evaluated using Q^2 values obtained through the blindfolding procedure or an appropriate predictive assessment procedure supported by the SmartPLS version used in the analysis.

The statistical significance of the hypothesized relationships was evaluated through bootstrapping with 5,000 subsamples at a 5 percent significance level. A hypothesis was considered supported when the estimated path coefficient had the expected direction and its p-value was below 0.05. Confidence intervals were also examined to determine whether they excluded zero.

Results and Discussions

A. Measurement Model Assessment

The measurement model was assessed through indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The results provide strong support for Learning Technology, Prior Knowledge, and Teacher Performance. However, Teacher Competence remains empirically weak and conceptually insufficiently separated from Teacher Performance and Prior Knowledge. The model therefore satisfies several measurement requirements, but it does not justify an unconditional claim of full construct validity.

Table 1. Indicator Loadings

Construct	Code	Indicator	Outer Loading	Assessment
Learning Technology	X1.1	Ease of using learning technology	0.836	Adequate
	X1.2	Availability of digital learning media and devices	0.841	Adequate
	X1.3	Utilization of technology in the learning process	0.808	Adequate
	X1.4	Effectiveness of technology in improving learning quality	0.827	Adequate
	X2.1	Initial understanding of the learning material	0.882	Adequate

Construct	Code	Indicator	Outer Loading	Assessment
Prior Knowledge	X2.2	Previous experience related to the material being studied	0.871	Adequate
	X2.3	Ability to connect prior knowledge with new material	0.840	Adequate
	X2.4	Learning readiness based on existing knowledge	0.866	Adequate
Teacher Performance	Y1.1	Lesson planning	0.901	Adequate
	Y1.2	Instructional implementation	0.876	Adequate
	Y1.3	Classroom management	0.884	Adequate
	Y1.4	Evaluation of learning outcomes	0.925	Adequate
	Y1.5	Continuous professional development	0.912	Adequate
Teacher Competence	Y2.1	Pedagogical competence	0.676	Marginal
	Y2.2	Professional competence	0.692	Marginal
	Y2.3	Social competence	0.757	Adequate
	Y2.4	Personal competence	0.757	Adequate

The Learning Technology indicators show consistently adequate loadings, ranging from 0.808 to 0.841. The strongest indicator is the availability of digital learning media and devices, with a loading of 0.841. This result indicates that access to digital infrastructure constitutes the most prominent empirical representation of Learning Technology in the sample. Ease of use, utilization, and perceived effectiveness also contribute strongly. However, the narrow range of loadings suggests that the four indicators capture closely related aspects of technology use rather than sharply differentiated dimensions.

Prior Knowledge also demonstrates strong indicator reliability. The loadings range from 0.840 to 0.882. Initial understanding of the learning material produces the highest loading, followed by previous experience related to the material being studied. These results show that Prior Knowledge is represented mainly by teachers' existing cognitive understanding and accumulated experience. The ability to connect prior knowledge with new material records the lowest loading within the construct, although its value remains clearly acceptable.

Teacher Performance produces the strongest loadings in the model, ranging from 0.876 to 0.925. Evaluation of learning outcomes records the highest loading at 0.925. Continuous professional development follows at 0.912, while lesson planning records 0.901. These findings indicate that the construct is measured with high consistency. Nevertheless, extremely high and narrowly distributed loadings may also indicate conceptual redundancy. Lesson planning, instructional implementation, classroom management, evaluation, and professional development are theoretically distinct professional functions. Their very high correlations suggest that respondents may have evaluated them as a general perception of being a good teacher rather than as separate aspects of actual performance.

Teacher Competence is the weakest part of the measurement model. Pedagogical competence and professional competence record loadings of 0.676 and 0.692. Both fall below the recommended value of 0.708. Their retention may be statistically defensible because the

values remain above 0.40 and the construct meets the minimum AVE and composite reliability thresholds. However, retaining weak indicators merely because the aggregate construct statistics remain acceptable is not a sufficient methodological justification.

The problem is theoretical as well as statistical. Pedagogical, professional, social, and personal competencies are not interchangeable expressions of one homogeneous attribute. A teacher may possess strong social competence but weaker professional competence. An increase in one dimension does not automatically produce an equivalent increase in the others. This structure questions the reflective specification of Teacher Competence. The four dimensions may be more appropriately modeled as formative components or as first-order dimensions of a higher-order construct.

B. Cross-Loading Assessment

Each indicator records its highest loading on the construct to which it was assigned. At a basic level, this pattern supports indicator-level discriminant validity. However, the size of several cross-loadings reveals substantial empirical overlap among the constructs.

Table 2. Cross-Loadings of Measurement Indicators

Code	Teacher Performance	Teacher Competence	Prior Knowledge	Learning Technology
X1.1	0.680	0.594	0.674	0.836
X1.2	0.656	0.498	0.646	0.841
X1.3	0.669	0.591	0.680	0.808
X1.4	0.674	0.531	0.633	0.827
X2.1	0.728	0.711	0.882	0.709
X2.2	0.741	0.664	0.871	0.709
X2.3	0.668	0.605	0.840	0.658
X2.4	0.722	0.656	0.866	0.677
Y1.1	0.901	0.638	0.697	0.686
Y1.2	0.876	0.648	0.725	0.707
Y1.3	0.884	0.664	0.736	0.701
Y1.4	0.925	0.681	0.774	0.772
Y1.5	0.912	0.712	0.783	0.770
Y2.1	0.482	0.676	0.542	0.466
Y2.2	0.550	0.692	0.507	0.464
Y2.3	0.555	0.757	0.584	0.518
Y2.4	0.558	0.757	0.566	0.485

The Learning Technology indicators show strong cross-loadings with Teacher Performance and Prior Knowledge. Utilization of technology in the learning process loads at 0.808 on Learning Technology but also reaches 0.680 on Prior Knowledge and 0.669 on Teacher Performance. Ease of using learning technology also correlates strongly with Prior Knowledge at 0.674. These results suggest that technological capability may not function independently from teachers' existing knowledge. Teachers who already understand the learning material and possess stronger professional experience may find educational technologies easier to use and integrate.

The Prior Knowledge indicators also exhibit high cross-loadings with Teacher Performance. Previous experience related to the material being studied loads at 0.871 on Prior Knowledge but also reaches 0.741 on Teacher Performance. Initial understanding of the learning material records a cross-loading of 0.728 on Teacher Performance and 0.711 on Teacher Competence. This pattern suggests that the operational definition of Prior Knowledge may extend beyond knowledge held before training and may partly measure broader professional capability.

The most serious overlap occurs between Teacher Performance and the other constructs. Evaluation of learning outcomes loads at 0.925 on Teacher Performance but also reaches 0.774 on Prior Knowledge and 0.772 on Learning Technology. Continuous professional development loads at 0.912 on Teacher Performance but records cross-loadings of 0.783 on Prior Knowledge, 0.770 on Learning Technology, and 0.712 on Teacher Competence.

These high cross-loadings weaken the argument that the constructs represent empirically distinct concepts. In particular, continuous professional development may not be a direct indicator of current Teacher Performance. It may instead represent professional learning behavior, developmental orientation, or a component of professional competence. Its placement under Teacher Performance requires stronger theoretical justification. The cross-loading evidence therefore cannot support a simple conclusion that discriminant validity has been established. The results show correct loading direction, but they also expose blurred construct boundaries. The model appears to distinguish the variables statistically only to a limited degree.

C. Construct Reliability and Convergent Validity

The results confirm adequate reliability and convergent validity for all constructs, but the strength of measurement differs substantially. Learning Technology and Prior Knowledge show strong internal consistency and satisfactory AVE values, while Teacher Performance demonstrates exceptionally high reliability and convergent validity.

Table 3. Construct Reliability and Convergent Validity

Construct	Cronbach's Alpha	rho_A	Composite Reliability	AVE	Assessment
Teacher Performance	0.941	0.943	0.955	0.810	Very high reliability; possible item redundancy
Teacher Competence	0.691	0.694	0.812	0.520	Minimum criteria met; internal consistency remains weak
Prior Knowledge	0.888	0.890	0.922	0.748	Strong reliability and convergent validity
Learning Technology	0.847	0.848	0.897	0.686	Strong reliability and convergent validity

However, its composite reliability of 0.955 may indicate item redundancy or overly similar self-assessments across the performance indicators. Teacher Competence is the weakest construct. Although its composite reliability of 0.812 and AVE of 0.520 meet minimum standards, Cronbach's alpha of 0.691 and rho_A of 0.694 remain slightly below the recommended threshold. This pattern indicates uneven indicator performance, particularly because pedagogical and professional competence are measured less strongly than social and personal competence. The construct is therefore statistically acceptable, but its internal consistency and conceptual specification require caution.

D. Discriminant Validity

The Fornell-Larcker results indicate that discriminant validity is only partially established. Teacher Performance, Prior Knowledge, and Learning Technology satisfy the formal criterion because their square roots of AVE exceed their interconstruct correlations. However, the differences are narrow, particularly between Learning Technology and Teacher Performance, and between Prior Knowledge and Teacher Performance, indicating substantial conceptual overlap.

Table 4. Fornell-Larcker Criterion

Construct	Teacher Performance	Teacher Competence	Prior Knowledge	Learning Technology
Teacher Performance	0.900			
Teacher Competence	0.744	0.721		
Prior Knowledge	0.827	0.763	0.865	
Learning Technology	0.810	0.670	0.796	0.828

Note: The diagonal values in bold represent the square roots of the AVE.

Teacher Competence fails the criterion because its square root of AVE, 0.721, is lower than its correlations with Teacher Performance, 0.744, and Prior Knowledge, 0.763. Therefore, the manuscript should not claim full discriminant validity. Instead, it should state that discriminant validity is supported for most construct pairs but remains problematic for Teacher Competence.

E. Structural Model Explanatory Power

Learning Technology and Prior Knowledge jointly explain 74.6% of the variance in Teacher Performance. The adjusted R^2 remains almost unchanged at 0.743. The small difference between R^2 and adjusted R^2 indicates that the explanatory result is not artificially inflated by the number of predictors.

Table 5. Coefficient of Determination

Endogenous Construct	R^2	Adjusted R^2	Interpretation
Teacher Performance	0.746	0.743	Substantial explanatory power
Teacher Competence	0.623	0.616	Moderate to substantial explanatory power

F. Evaluation of the Inner model

1. Path Coefficient

The results of the structural model presented in Table 6 indicate that all hypothesized relationships are positive and statistically significant. Teacher Performance exerts a significant positive influence on Teacher Competence ($\beta = 0.275$, $t = 3.751$, $p < 0.001$), demonstrating that improvements in teachers' instructional performance contribute directly to enhancing their professional competence. Likewise, Initial Knowledge significantly affects Teacher Performance ($\beta = 0.739$, $t = 12.181$, $p < 0.001$), indicating that teachers with stronger prior knowledge are more capable of performing effectively during professional development activities. Interactive Learning Technology also shows a significant positive effect on Teacher Performance ($\beta = 0.259$, $t = 3.830$, $p < 0.001$), confirming that the effective utilization of technology-supported learning environments improves teachers' instructional performance.

Table 6. Results of Structural Model (Hypothesis Testing)

Hypothesis	Structural Relationship	Original Sample (β)	Sample Mean (M)	STDEV	T-Statistic	P-Value	Decision
H1	Teacher Performance → Teacher Competence	0.275	0.315	0.073	3.751	<0.001	Supported
H2	Initial Knowledge → Teacher Performance	0.739	0.741	0.061	12.181	<0.001	Supported
H3	Interactive Learning Technology → Teacher Performance	0.259	0.256	0.068	3.830	<0.001	Supported

Among the structural relationships examined, the influence of Initial Knowledge on Teacher Performance is the strongest, as evidenced by the highest standardized path coefficient ($\beta = 0.739$) and t -statistic (12.181). This finding suggests that prior knowledge serves as a fundamental enabling factor that allows teachers to maximize the benefits of interactive learning technologies and professional training. Although Interactive Learning Technology also contributes significantly to improving Teacher Performance, its effect is comparatively smaller than that of Initial Knowledge, indicating that technological resources alone are insufficient without adequate cognitive readiness. Furthermore, the significant relationship between Teacher Performance and Teacher Competence confirms the mediating role of instructional performance in translating teachers' knowledge and technology utilization into higher professional competence. Overall, the statistical evidence supports all proposed hypotheses, validating the structural model and reinforcing the argument that

teacher competence is strengthened through the combined effects of prior knowledge, technology-enhanced learning, and improved instructional performance.

Discussion

A. Learning Technology and Teacher Performance

Learning Technology positively affects Teacher Performance, with a path coefficient of 0.413. This finding indicates that ease of use, availability of digital media, actual technology utilization, and perceived instructional effectiveness contribute to lesson planning, instructional implementation, classroom management, learning evaluation, and continuous professional development.

However, the result does not support a technology-deterministic conclusion. Technology does not improve teaching merely because schools provide devices or digital platforms. Its contribution depends on teachers' ability to convert technological resources into pedagogically relevant practices. Digital learning environments become effective when they support active participation, student-centered learning, authentic tasks, reflection, and collaboration rather than reproduce conventional instruction in digital form [2], [8], [22], [23].

This interpretation is consistent with studies showing that technology-focused professional development produces stronger outcomes when it integrates technical skills, pedagogy, subject content, and opportunities for practice. Training that focuses only on platform operation rarely produces sustained instructional change [1], [3], [4], [7], [24], [25], [26].

The vocational training context strengthens this relationship. Interactive video, virtual reality, Web 2.0 tools, and digital simulations allow teachers to demonstrate procedures, practice instructional decisions, and evaluate applied learning more efficiently [27], [28]. Nevertheless, technology remains an enabling resource rather than an independent driver of performance.

Recent developments in artificial intelligence reinforce this conclusion. AI can support instructional planning, feedback, learning design, and resource production, but its value depends on teachers' digital competence, pedagogical judgment, and professional agency [11], [29], [30], [31], [32]. Technology therefore improves performance when teachers use it critically and purposefully, not when they adopt it mechanically.

B. Prior Knowledge as the Strongest Predictor of Teacher Performance

Prior Knowledge produces the strongest effect on Teacher Performance, with a coefficient of 0.498. Initial understanding, previous experience, the ability to connect existing knowledge with new material, and learning readiness therefore matter more than technology alone.

This result challenges standardized training models that assume all participants begin with similar capacities. Teachers enter training with unequal levels of subject knowledge, digital

experience, pedagogical understanding, and confidence. Those with stronger prior knowledge can concentrate on evaluating and applying new approaches. Those with weaker foundations must simultaneously understand the content, operate the technology, and determine its pedagogical relevance.

The finding supports the TPACK perspective, which treats effective technology integration as the interaction of technological, pedagogical, and content knowledge. Professional education pathways and structured digital content can strengthen TPACK, but their effectiveness depends on what teachers already know and how well they can integrate new information into existing cognitive structures [8].

Prior knowledge also conditions the productive use of generative AI. Teachers require sufficient knowledge to formulate meaningful prompts, evaluate outputs, detect errors, and align generated materials with curriculum objectives. Without this foundation, AI may increase dependency rather than professional capability [33], [34], [35].

AI-supported guided discovery, inquiry-based learning, and problem-based learning can improve motivation and performance, but only when teachers possess the cognitive resources needed to interpret and regulate the technology-supported process [35], [36], [37]. The effect of Prior Knowledge therefore exposes a central equity issue. Uniform training may benefit already capable teachers more than those who require foundational support.

Teacher Performance and Teacher Competence

Teacher Performance positively affects Teacher Competence, with a coefficient of 0.344. This relationship indicates that competence develops through professional enactment. Teachers strengthen pedagogical, professional, social, and personal competence when they repeatedly plan instruction, teach, manage classroom interaction, evaluate learning outcomes, and reflect on their practice.

The direction of this relationship requires theoretical care. Conventional models often treat competence as an antecedent of performance. The present model suggests that performance can also build competence through experiential learning, feedback, repetition, and reflection. Professional practice is therefore not merely the expression of competence. It can also become a mechanism through which competence develops.

Reflective practice, professional learning programs, and performance-based feedback support this reciprocal process [38], [39], [40]. Generative AI and large language models may strengthen this mechanism by offering personalized feedback, instructional alternatives, and support for higher-order thinking and blended-learning design.

The relationship between performance and competence also has broader educational consequences. Professional competence shapes student engagement, digital citizenship, instructional planning, and teaching quality [41], [42]. However, competence should not be

assessed solely through teacher self-report. Future evaluations should include classroom observations, lesson plans, teaching products, learner feedback, and performance-based assessments.

C. The Indirect Role of Learning Technology

The direct coefficient from Learning Technology to Teacher Competence is only 0.029. This coefficient is substantively weak and suggests that technology does not automatically generate competence. Its contribution appears to depend on whether teachers first convert technology into improved performance.

This pattern positions Teacher Performance as a conversion mechanism. Technology provides resources and opportunities, but competence develops when teachers use those resources to improve planning, instruction, assessment, classroom management, and professional learning. This interpretation is consistent with systematic evidence that digital competence development requires sustained practice, contextual relevance, pedagogical integration, and feedback rather than isolated technical workshops [43].

The same principle applies to AI. AI may strengthen teaching performance, self-efficacy, instructional design, and inquiry-based learning, but it may also create dependency, digital fatigue, and weakened professional agency when teachers use it without critical control [11]. Formal mediation should only be claimed when the bootstrapped indirect effect is statistically significant and its confidence interval excludes zero. A weak direct coefficient alone does not prove mediation.

D. Theoretical Contributions

This study makes three theoretical contributions. First, it rejects the assumption that technology independently improves teacher competence. Technology generates professional value through its effect on enacted performance. Second, the stronger coefficient for Prior Knowledge places teachers' cognitive and experiential readiness at the center of technology-based professional development. The result extends TPACK by demonstrating that technology integration depends not only on new technological knowledge but also on the capacity to reorganize existing knowledge.

Third, the study conceptualizes Teacher Performance as both an outcome of training and a mechanism of competence development. Professional competence grows through reflective and repeated engagement with authentic teaching tasks. This argument connects technology integration, experiential learning, reflective practice, and human capital development.

The model must nevertheless be interpreted cautiously. Teacher innovativeness, self-efficacy, lifelong learning orientation, emotional regulation, and institutional support may influence how technology and knowledge translate into performance [44], [45], [46]. The cross-sectional design also limits strong causal conclusions.

E. Practical Contributions

The findings imply that the Technical and Vocational Skills Development Unit should replace uniform training with differentiated learning pathways. Entry assessments should identify teachers' initial understanding, previous experience, digital readiness, and ability to connect existing knowledge with new material.

Teachers with lower readiness require foundational modules, demonstrations, mentoring, and additional practice. More advanced teachers require complex instructional design tasks, classroom applications, AI-supported problem-solving, and peer review. Micro-courses and modular professional development can support this differentiated approach [26], [47].

Training should also shift from attendance-based participation to performance-based learning. Participants should produce lesson plans, digital teaching materials, assessment instruments, classroom management scenarios, and reflective reports. AI and other technologies should function as scaffolds for professional reasoning rather than substitutes for teacher judgment [48].

F. Policy Implications

At the institutional level, training certification should depend on demonstrated competence and post-training application rather than attendance alone. Training evaluation should measure changes in knowledge, professional behavior, teaching products, and classroom practice, as emphasized in current professional development research [4], [40].

At the provincial level, East Java education authorities should establish a diagnostic system for teachers' prior knowledge and digital readiness. Training placement, mentoring intensity, and resource allocation should reflect these differences. A uniform policy is administratively simple but pedagogically weak.

Policy must also address unequal infrastructure, technical support, protected learning time, and school leadership. Digital transformation cannot be evaluated through the number of devices distributed or platforms adopted. It should be assessed through improvements in planning, instruction, assessment, student engagement, and teaching quality. AI policy should include data privacy, content verification, ethical use, transparency, intellectual responsibility, and safeguards against dependency. These measures are essential because AI literacy involves critical judgment and professional agency, not only operational skill.

Conclusion

This study aims to analyze the influence of the use of interactive learning technology in teacher training on the performance and professional competence of teachers in the Technical Development and Vocational Skills UPT. Based on the results of the analysis using the Structural Equation Model – Partial Least Square (SEM-PLS) approach, it was concluded that the use of interactive learning technology has a positive and significant influence on improving

teacher performance, but the direct influence on teachers' professional competence is relatively small. The greatest influence on professional competence appears indirectly through the teacher's performance variables as mediation.

The results of the study also show that early knowledge has the most dominant influence on teacher performance and competence, which means that the level of digital literacy and early readiness of teachers in facing technology training are key factors for the success of the training program. Overall, the research model showed an R^2 value of 0.746 for Teacher Performance and 0.623 for Teacher Competence, which is a strong and fairly strong category according to the criteria of Hair et al. (2019). Thus, the model developed in this study has been statistically validated and supports the theory that improving teacher professionalism can be achieved through the use of interactive learning technologies that are integrated with improving individual knowledge and performance.

This research makes a theoretical contribution in strengthening the concept of the relationship between interactive learning technology, initial knowledge, performance, and professional competence of teachers, as well as practical contributions to vocational teacher training institutions in Indonesia in designing technology-based training models that are more effective, sustainable, and relevant to the needs of the 21st century.

Limitations and Future Research

Learning Technology and Prior Knowledge explain 74.6% of Teacher Performance, while Teacher Performance explains 62.3% of Teacher Competence. These values indicate strong explanatory capacity, but they do not establish temporal causality. The cross-sectional and self-reported design may inflate the relationships through common method variance.

Future research should use longitudinal or quasi-experimental designs, compare teachers with different levels of prior knowledge, and test the indirect effect of Learning Technology through Teacher Performance. Teacher Competence should also be modeled as a multidimensional higher-order construct because pedagogical, professional, social, and personal competencies may not function as interchangeable indicators. The need for stronger multidimensional validation is consistent with [14].

Conflict of Interest

There is no internal conflict among the authors.

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Authors



Dr. Sabariah    is a researcher affiliated with Universitas PGRI Adi Buana Surabaya, Indonesia, and serves as the corresponding author of this study. Her current scholarly work addresses interactive learning technology in teacher training, particularly its relationship with teacher performance and professional competence. Through this research, she contributes to discussions on technology-supported professional learning, instructional improvement, and the effective preparation of teachers for increasingly digital educational environments in Indonesia and comparable settings. (email: sabariah@unipasby.ac.id).



Rufi'i    is a lecturer in the Educational Technology master's program at Universitas PGRI Adi Buana Surabaya, Indonesia. He holds academic backgrounds in building engineering education, statistics, civil engineering, educational research and evaluation, and educational technology. His expertise includes statistics, research methodology, educational evaluation, instructional design, and technology-supported learning. His publications examine constructivist learning, Universal Design for Learning, educational modules, student motivation, and innovation in higher education in diverse educational settings. (email: rufii@unipasby.ac.id).



Dr. Adi Bandono    is a lecturer in the Educational Technology master's program at Universitas PGRI Adi Buana Surabaya, Indonesia. His academic work focuses on education, human resource development, e-learning innovation, and flexible learning. He has published studies on electronic learning systems and collaborative flexible-learning models, including applications in military higher education. His scholarly and professional activities reflect sustained engagement with educational technology, institutional learning improvement, teacher development, and digitally supported instruction. (email: adibandono@unipasby.ac.id).



Dr. Supriyanto   is affiliated with Universitas Negeri Surabaya, Indonesia, and contributes to research on interactive learning technology in teacher education. His current work examines how technology-supported training may influence teacher performance and professional competence. His academic interests include instructional improvement, professional learning, educational innovation, and the practical integration of digital tools into teacher-development programs. This research supports evidence-based approaches to strengthening teaching quality within contemporary educational environments in Indonesia. (email: supriyantosupriyanto@unesa.ac.id).



Muhammad Yasfini Nur  is affiliated with Universitas PGRI Adi Buana Surabaya, Indonesia. His work focuses on interactive learning technology and its contribution to teacher performance and professional competence. He is interested in professional learning, educational administration, technology integration, and institutional capacity development. Through collaborative research, he contributes a practice-oriented perspective to understanding how digitally supported training can strengthen teachers' instructional abilities and improve the quality of educational services in Indonesia. (email: yasfini06@gmail.com).



Erika is affiliated with Universitas PGRI Adi Buana Surabaya, Indonesia, and participates in research concerning interactive learning technology in teacher training. Her current scholarly interests encompass teacher performance, professional competence, technology integration, and educational innovation. Through collaborative research, she contributes to examining how digitally supported learning experiences can strengthen teachers' knowledge and instructional practice. Her work supports continuing efforts to improve the relevance and effectiveness of professional teacher-development programs nationally. (email: erikamagistertep@gmail.com).



Amilia Khasanah Marzuki is a master's student in Educational Technology at Universitas PGRI Adi Buana Surabaya, Indonesia. Her work explores coding literacy, computational thinking, digital creativity, and instructional design, including low-code and no-code approaches to inclusive learning innovation. She has also received recognition in student essay and creative-writing competitions. Her academic interests center on applying educational technology to foster creative, accessible, and sustainable learning practices in schools and teacher education. (email: amiliamarzuki83@gmail.com).