Longitudinal Analysis of Sustainable Impact of e-Learning Integration on Academic Capabilities, Critical Thinking Skills, and Digital Behavior of Automotive Engineering Students

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***Abstract*—The rapid advancement of digital technology has revolutionized global education, with e-learning emerging as a foundation of modern pedagogical approaches. In automotive engineering, e-learning integration creates opportunities for enhanced learning while presenting unique challenges. This field demands theoretical knowledge and practical skills, making it ideal for testing e-learning's multifaceted impact. Significant gaps remain in understanding the longitudinal effects of e-learning integration, particularly regarding critical thinking development and digital behavior transformation. Through a longitudinal approach, this study examines the sustainable impact of e-learning integration on academic capabilities, critical thinking skills, and digital behavior of automotive engineering students. The research investigates relationships between e-learning usage patterns, digital learning interaction, critical thinking development, digital behavior transformation, and long-term learning outcomes. The study employed a longitudinal quantitative design with data collection at three-time points: baseline, six months post-implementation, and twelve months post-implementation. The population consisted of vocational education students from 2019–2023 cohorts, with 225 respondents using stratified random sampling. A 40-item survey measured eight variables using Structural Equation Modeling (SEM) with SmartPLS 4 software. Results showed excellent validity and reliability (outer loading 0.788–0.897, Cronbach's alpha >0.885, composite reliability 0.916–0.936). The structural model demonstrated strong predictive power (R-square >0.68). Social Support showed a dominant influence on Digital Learning Interaction ($\beta = 0.825, p < 0.001$), while E-Learning Usage Patterns strongly impacted Digital Behavior Transformation ($\beta = 0.682, p < 0.001$). Critical Thinking Development significantly influenced Continuous Learning Outcomes ($\beta = 0.431$, $p < 0.001$), demonstrating sustainable academic capability enhancement. Findings indicate that e-learning integration produces sustainable benefits through digital behavior transformation and critical thinking development, with social Support and digital skills as key success factors.**

***Keywords*—quality education, e-learning integration, critical thinking development, digital behavior transformation, longitudinal analysis**

I. Introduction

The rapid advancement of digital technology has revolutionized global education, with e-learning emerging as a foundation of modern pedagogical approaches [1, 2]. Digital transformation in education was significantly accelerated by the COVID-19 pandemic, which forced educational institutions worldwide to adopt digital learning platforms on an unprecedented scale [3, 4]. In Indonesian vocational education, e-learning has become a strategic imperative that responds to the need for learning continuity and prepares graduates to face the increasingly competitive demands of Industry 4.0 [5, 6].

The automotive engineering discipline faces unique transformation challenges in this era of digitalization [7, 8]. As a field traditionally relied on hands-on learning and hands-on practice, integrating e-learning platforms in automotive engineering presents a paradox between the need for practical experience and the potential of digital technology to improve learning effectiveness [9, 10]. The field demands a complex synthesis of deep theoretical knowledge, precise practical skills, and dynamic technological adaptability, making it an ideal context for testing the multidimensional impact of e-learning integration [11]. As the Industry 4.0 revolution continues to reshape the automotive landscape through technologies such as autonomous vehicles, electrification, and Internet of Things (IoT) integrated systems, automotive engineering students must develop not only traditional technical competencies but also critical thinking skills, digital literacy, and continuous learning capacity that will be determinants of their career success [12].

The e-learning research literature shows a growing consensus that digital learning platforms can positively affect student engagement, content accessibility, and, in some cases, academic performance [13]. Recent meta-analyzes show that e-learning can produce outcomes equal to or superior to traditional learning when implemented with the right pedagogical design [14]. However, most of this empirical evidence comes from short-term studies that measure the direct impact of e-learning implementations, with little attention to the sustainability of the long-term benefits and transformations that may occur for students. A more significant gap lies in understanding the longitudinal effects of e-learning integration, particularly its impact on developing high-level cognitive skills such as critical thinking and fundamental transformations in students' digital behavior [15].

Previous research has tended to adopt a fragmented approach that tests variables such as user satisfaction, technical acceptance, or academic performance separately, failing to capture the complex learning ecosystem and interrelated relationships that evolve. These methodological constraints lead to an incomplete comprehension of how e-learning creates value within vocational education. Moreover, the majority of research was undertaken within the framework of general higher education or distance learning, with minimal representation of vocational education programs that possess distinct characteristics related to practical orientation, industry relevance, and the necessity for a close integration of theory and practice [16].

The primary research gap is the absence of a comprehensive theoretical framework to elucidate the causal processes by which e-learning induces a lasting alteration in students' learning capacity. The Technology Acceptance Model (TAM) and analogous models provide insights into technology acceptance; nevertheless, they insufficiently account for how the sustained use of e-learning platforms might alter students' cognitive processes, learning behaviors, and long-term academic outcomes. Likewise, although Social Cognitive Theory (SCT) provides a framework for understanding learning within social settings, its applicability in complex and evolving digital learning environments has not been well examined in vocational education [17, 18].

This research addresses these basic constraints by employing a comprehensive longitudinal strategy to assess the sustainable benefits of integrating e-learning into automotive engineering vocational education. This research formulates a framework that examines the intricate link between e-learning use patterns, digital learning interactions, critical thinking growth, digital behavior change, and long-term learning outcomes through the theoretical integration of Social Cognitive Theory (SCT) and the Technology Acceptance Model (TAM). This method facilitates a comprehensive understanding of how e-learning facilitates knowledge transfer and promotes essential changes in students' information processing, technology interaction, and lifelong learning capabilities [19, 20].

This research aims to evaluate the sustainable effects of e-learning integration on the academic performance, critical thinking abilities, and digital behavior change of automotive engineering students using a longitudinal methodology. This study aims to identify the primary factors influencing the effectiveness of e-learning in vocational education, examine the mediating mechanisms linking e-learning to learning outcomes, and develop predictive models to inform optimal e-learning implementation strategies. This project seeks to enhance theoretical comprehension of learning processes in the digital era and to facilitate the creation of evidence-based learning systems.

The significance of this research extends beyond academic contributions to substantial practical implications for multiple stakeholders in the vocational education ecosystem. For educational institutions, the findings of this research can inform strategic planning for learning technology investments, curriculum design that optimizes digital integration, and the development of student support systems that are responsive to digital learning needs. For education policymakers, this study provides an evidence base for policies that support the digitalization of vocational education that is sustainable and effective. For students and instructors, the insights from this research can guide optimizing digital learning experiences and developing competencies relevant to the industrial era 4.0.

In a broader context, this research contributes to the knowledge about digital transformation in education and provides a model that can be adapted for other vocational education contexts. As educational institutions in Indonesia and other developing countries continue to invest in digital learning infrastructure, evidence-based insights into long-term benefits, risk factors, and optimal implementation strategies are becoming increasingly valuable to ensure maximum return on investment and achieve sustainable learning goals.

II. Literature Review

A. Theoretical Integration Framework

This study uniquely synthesizes Social Cognitive Theory (SCT) [21] and Technology Acceptance Model (TAM) [22] to create a comprehensive framework for understanding e-learning effectiveness in vocational education. While TAM explains technology adoption through perceived usefulness and ease of use [22], it lacks consideration of social and motivational factors. Conversely, SCT emphasizes learning through social observation and self-efficacy [21] but does not directly address technology acceptance mechanisms. Previous attempts to integrate theories for e-learning contexts [23] have not specifically addressed vocational engineering education. Our integration bridges this gap by positioning SCT constructs as antecedents to TAM variables.

Table 1 illustrates this integrated framework, showing how self-efficacy (operationalized as Digital Skills) influences perceived ease of use [21, 22], outcome expectations (Learning Motivation) shape perceived usefulness [22], and environmental factors (Social Support) affect behavioral intention [21]. This synthesis reveals that technology acceptance in educational contexts is fundamentally a socio-technical process requiring both technological readiness and social-cognitive support systems [23].

Table 1. Theoretical construct integration and operationalization

SCT Construct	TAM Construct	Study Variable	Integration Mechanism
Self-efficacy	Perceived Ease of Use	Digital Skills (DS)	Higher digital self-efficacy reduces perceived complexity
Outcome Expectations	Perceived Usefulness	Learning Motivation (LM)	Positive expectations enhance perceived learning value
Environmental Factors	Behavioral Intention	Social Support (SS)	Peer/instructor support increases usage intention
Observational Learning	Actual Use	E-Learning Usage Patterns	Social modeling influences platform engagement
Behavioral Capability	Performance	Critical Thinking & Digital Behavior	Sustained use develops new capabilities

This integrated framework advances theoretical understanding by demonstrating that successful e-learning adoption requires simultaneous attention to technological acceptance and social-cognitive development processes.

B. The DeLone & McLean Model and e-Learning Evaluation

E-learning has become a fundamental aspect of the higher education system; nonetheless, its application requires considerable expenditure of time, effort, and financial resources [24]. Numerous studies assessing the efficacy of e-learning have been undertaken in both developed and developing nations; nonetheless, obstacles persist in pinpointing the characteristics that influence its performance [25].

The DeLone and McLean (D&M) model of information systems success, developed in 1992, has emerged as the preeminent assessment paradigm in the information systems literature. In 2003, this model was enhanced by including service quality as an additional dimension and amalgamating individual and organizational effects into a unified net benefit variable. The D&M model has been extensively used to assess the efficacy of e-learning, with 92 significant papers using this approach in the e-learning environment between 2010 and 2020 [26].

In higher education, e-learning is used not just for distance learning programs but has also been deliberately incorporated into on-campus and hybrid learning environments. Higher education institutions are utilizing e-learning to achieve learning outcomes comparable to those of conventional in-person education while offering flexibility, accessibility, and personalization through information and communication technology [27].

Adverse circumstances, such as natural disasters, pandemics, and armed conflicts, may impede education and result in missed learning opportunities. E-learning is the most effective method to ensure the sustainability of learning in this context. In wartime, educational participants face unique challenges, including relocation, restricted internet access, diverse curfews, and fluctuating security levels, which can hinder the e-learning process [28].

A literature assessment reveals a research gap, as the majority of studies focus solely on the COVID-19 pandemic, while research on wartime contexts remains limited. Among the few research completed during the conflict, only one in Yemen used the D&M model. However, it failed to account for wartime circumstances as a variable affecting the efficacy of e-learning systems. Research is required to develop a model that expands the D&M framework to assess the efficacy of e-learning through the lens of learning outcomes, including the variable of wartime circumstances as a novel component that affects e-learning success.

C. Integration of e-Learning in Technical Education

The integration of e-learning in technical education has evolved from a simple content delivery system to a sophisticated platform that supports interactive learning, collaboration, and skill development. E-learning platforms in engineering education can effectively complement traditional instructional methods, particularly in acquiring theoretical knowledge and developing problem-solving skills [29].

In automotive engineering, e-learning has shown tremendous potential in system diagnostics, theoretical foundations, and safety protocols. The visual and interactive nature of modern e-learning platforms aligns with the learning preferences of engineering students, who often benefit from multimedia presentations and simulation-based learning experiences [30].

D. Development of Critical Thinking through Digital Learning

Critical thinking abilities are essential for engineering professionals, including the capacity to analyze complex situations, assess various options, and make informed decisions in ambiguous situations. The correlation between e-learning and the enhancement of critical thinking has garnered significant academic attention, with varied results across several educational settings [31].

Recent research suggests that a well-structured e-learning environment can enhance critical thinking through interactive case studies, collaborative problem-solving tasks, and reflective learning activities. The asynchronous characteristics of several e-learning systems enable students to engage with the content at their own pace, potentially promoting enhanced reflection and analysis [32].

E. Digital Behavior Transformation

The digital behavioral transformation includes changes in how individuals interact with technology, process digital information, and integrate digital tools into their daily academic and professional activities. This transformation is relevant for engineering students as they prepare for careers in an increasingly digitized industry [33].

Research shows that continued exposure to an e-learning environment can lead to increased digital literacy, increased comfort with technology-mediated communication, and greater proficiency in using digital tools for learning and problem-solving. These behavioral changes often extend beyond the academic context, affecting how students approach personal and professional challenges [34].

F. Long-Term Learning Outcomes

The sustainability of learning outcomes is a critical concern in educational research. While many studies show the immediate benefits of e-learning interventions, fewer have tested whether these benefits persist over time and contribute to long-term academic and professional success. Longitudinal studies in this area show that the benefits of e-learning integration can increase over time, particularly as students develop self-study skills and maintain engagement with digital learning resources beyond formal course requirements [35].

Rather than exhaustively reviewing all e-learning literature, we focus on three critical gaps our study addresses. Despite extensive e-learning research, longitudinal investigations in vocational education remain remarkably scarce. A systematic review of 92 studies using the DeLone & McLean model [26] found only 7% employed longitudinal designs, with none focusing on vocational contexts. Most studies capture single time points through cross-sectional designs [14], missing how digital competencies evolve over extended periods. The few existing longitudinal studies examine general higher education [36] where learning trajectories differ fundamentally from vocational education's emphasis on practical skill development. This gap prevents understanding whether e-learning benefits sustain, intensify, or decay over time in technical education contexts.

Current research typically applies either Social Cognitive Theory (SCT) or Technology Acceptance Model (TAM) in isolation, missing their potential synergy [21, 22]. TAM studies emphasize technology adoption factors—perceived usefulness, ease of use—without considering social learning mechanisms essential in collaborative engineering education [30]. Conversely, SCT research examines self-efficacy and observational learning while overlooking technology-specific factors influencing platform engagement [15]. No studies have integrated both theories to comprehensively explain e-learning effectiveness in engineering education, where social collaboration and technology mastery prove equally critical for success.

Existing literature predominantly measures immediate, surface-level outcomes—grades, satisfaction scores, engagement metrics—while neglecting fundamental behavioral transformations. Digital behavior transformation, defined as lasting changes in how students seek information, solve problems, and collaborate using digital tools, remains unmeasured in vocational education research. Industry 4.0 demands graduates with fundamentally transformed digital behaviors enabling continuous adaptation to emerging technologies, not merely technical knowledge or platform familiarity. This oversight ignores employers' primary concern: developing professionals whose digital behaviors align with modern workplace requirements.

Our study directly addresses these gaps through: (1) a 12-month longitudinal design capturing e-learning impact evolution, (2) novel SCT-TAM theoretical integration providing comprehensive explanatory framework, and (3) explicit measurement of digital behavior transformation as a distinct, critical outcome variable alongside traditional academic metrics.

III. Methods

A. Research Design

This research employed a longitudinal quantitative approach to measure e-learning's sustained impact. We collected data at three points: baseline (T1), six months (T2), and twelve months (T3). This timeline captured both immediate effects and long-term transformations while maintaining participant retention.

Our population included 225 automotive engineering students from 2019–2023 cohorts. We selected participants using stratified random sampling to ensure each cohort's representation. Table 2 shows the sample distribution.

We developed a 40-item survey measuring eight variables on 5-point Likert scales. Each variable included five indicators validated through pilot testing. The survey took approximately 15 minutes to complete, reducing respondent fatigue while ensuring comprehensive data collection [35, 36].

Table 2. Variables and indicators

Variable	Type	Indicator	Main Measurement Area
E-Learning Usage Patterns (EUP)	Independent	EUP.1	Frequency of platform utilization
		EUP.2	Resource accessibility
		EUP.3	Use of collaboration
		EUP.4	Study organization
		EUP.5	Learning efficiency
Digital Learning Interaction (DLI)	Mediation	DLI.1	Discussion participation
		DLI.2	Quality of peer interaction
		DLI.3	Adequate communication space
		DLI.4	Instructor communication
		DLI.5	Learning engagement
Critical Thinking Development (CTD)	Dependent	CTD.1	Depth of problem analysis
		CTD.2	Critical evaluation skills
		CTD.3	Argument scoring
		CTD.4	Identify solutions
		CTD.5	Data analysis capabilities
Digital Behavior Transformation (DBT)	Dependent	DBT.1	Daily use of technology
		DBT.2	Platform trust
		DBT.3	Online information search
		DBT.4	Changes in technological interaction
		DBT.5	Digital platform skills
Continuous Learning Outcomes (CLO)	Dependent	CLO.1	Post-course skills development
		CLO.2	Access career-relevant
		CLO.3	Workplace knowledge applications
		CLO.4	Technology-industry relevance
		CLO.5	Broader learning perspective
Learning Motivation (LM)	Control	LM.1	Platform-based motivation
		LM.2	Personal achievements
		LM.3	Material interests
		LM.4	Progress-based motivation
		LM.5	Goal setting
Digital Skills (DS)	Moderating	DS.1	Technology trust
		DS.2	Software accessibility
		DS.3	Application skills
		DS.4	Technical troubleshooting
		DS.5	Convenience with digital technology
Social Support (SS)	Moderating	SS.1	Peer support
		SS.2	Instructor support
		SS.3	Family support
		SS.4	Troubleshooting assistance
		SS.5	Environmental focus support

B. Population and Sample

The research population consists of vocational education students who have extensively utilized the e-learning system. The group comprises students from many generations who have used digital learning tools for a minimum of one semester. The demographic comprises active and regular students with sufficient access to technology who are eager to engage in research.

The research used a stratified random sampling method with a division based on the student class. This method was chosen to ensure the representativeness of each batch, control for the variation of e-learning experiences, and allow generalization of research results in the context of vocational education. Students are divided into five groups based on the 2019–2023 entry batch. The class of 2019 has the longest e-learning experience and has experienced a transition from traditional practicum learning to digital learning. The class of 2020 experienced mixed learning between field practice and balanced e-learning. The 2021 and 2022 batches use a more mature e-learning system with stable virtual practicum integration. The Class of 2023 is a native digital learner who directly uses the most developed vocational e-learning system with sophisticated practice simulations [37].

The total sample was set at 225 respondents who met the requirements of SEM analysis with a ratio of 5:1 between the number of samples and the estimated parameters. The sample was determined for each stratum of the batch with consideration of representativeness and availability of respondents, namely the class of 2019, as many as 34 students; the class of 2020, as many as 43 students; the class of 2021 as many as 52 students, the class of 2022 as many as 56 students, and the class of 2023 as many as 40 students [38, 39].

The sampling process begins with obtaining a complete list of students from the academic department. Then, a random selection was performed in each stratum using statistical software, and a 10% reserve sample was prepared to overcome non-response. Respondents were recruited through official communication by providing research information and informed consent [40]. Participants who can participate in the research are active vocational education students of the 2019–2023 class who have used e-learning for at least 2 semesters, have adequate internet access, and are willing to participate in data collection at three different times. Students on leave, transfer students without adequate e-learning experience, or who cannot be contacted will be excluded from the study.

C. Data Collection Instruments

Data collection used comprehensive survey instruments explicitly developed for this research. The instrument incorporated validated scales from existing literature where available and included newly created items to address unique aspects of the research question. The survey instrument consisted of eight main sections corresponding to the research variables, with each section containing five items measured on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The complete instrument included 40 items designed to maintain reasonable turnaround times while ensuring comprehensive measurements of all constructs.

D. Variables and Indicators

This study examines eight key variables categorized based on their role in the developed structural model. The main variables of the study include five constructs that are the focus of the analysis of the sustainable impact of e-learning integration. E-Learning Usage Patterns (EUP) are independent variables that measure the pattern of use of digital learning platforms by students, including frequency of utilization, accessibility of resources, use of collaboration features, study organization, and learning efficiency [9]. Digital Learning Interaction (DLI) is a mediation variable that evaluates the quality of interaction in a digital learning environment, including discussion participation, quality of interaction with peers, adequacy of communication spaces, communication with instructors, and learning engagement [41]. Critical Thinking Development (CTD) and Digital Behavior Transformation (DBT) are dependent variables that measure the primary outcomes of e-learning integration [7, 8].

CTD evaluates the development of critical thinking skills through depth of problem analysis, essential evaluation skills, argument assessment, solution identification, and data analysis skills. DBT analyzes the transformation of students' digital behavior, which includes daily use of technology, trust in platforms, online information searches, changes in technological interactions, and digital platform skills. Continuous Learning Outcomes (CLO) are dependent variables that measure continuous learning outcomes, including post-course skill development, access to career-relevant content, knowledge application in the workplace, technology-industry relevance, and broader learning perspectives [42].

The control and moderating variables consist of three constructs that affect relationships in structural models. Learning Motivation (LM) is a control variable that measures platform-based student learning motivation, personal achievement, interest in the material, progress-based motivation, and goal setting [43]. Digital Skills (DS) is a moderating variable that evaluates trust in technology, software accessibility, application skills, technical troubleshooting, and comfort with digital technology [44]. Social Support (SS) is a moderating variable that analyzes support from peers, instructors, family, troubleshooting assistance, and environment-focused support that affects students' digital learning effectiveness [45].

E. Structural Equation Modeling (SEM) Path Analysis

The SEM methodology was employed to assess the proposed relationship among the variables in this study. The SEM framework was optimal because it allowed for the concurrent analysis of multiple interactions while accommodating measurement errors and intricate interdependencies among variables. The model specification included both measurement and structural components, with the measurement model defining the link between the observed indicators and the latent constructs to ensure that each variable accurately reflected its intended meaning. The structural model outlined the proposed relationships among the latent components, including direct effects, indirect effects mediated by intervening factors, and moderating effects [38, 39].

Data analysis was carried out through four systematic stages. The first stage was the initial analysis, which included descriptive statistics and data filtering, analysis and handling of missing data, and assumption testing for multivariate analysis. The second stage evaluated the measurement model by analyzing confirmatory factors for each construct, assessing reliability and validity, and evaluating suitability and refinement. The third stage was structural model testing, which included full structural model estimation, hypothesis testing, effect size calculations, mediation, and moderation analysis. The fourth stage was longitudinal analysis for cross-temporal stability assessment, change trajectory modeling, and time-invariant relationship testing.

Fig. 1 shows the conceptual framework of the research that illustrates the structural relationships between constructs in the sustainable impact model of e-learning integration. This model integrates eight constructs categorized based on their roles: antecedent variables [46] (Social Support, Digital Skills, Learning Motivation), mediator variables [47] (Digital Learning Interaction, E-Learning Usage Patterns), and outcome variables [48] (Critical Thinking Development, Digital Behavior Transformation, Continuous Learning Outcomes).

The model employs two forms of notation to illustrate the relationships between variables. Solid lines denote a hypothesized direct link, grounded in theory, that illustrates the primary causal pathways in structural models. The dotted line illustrates a moderating relationship in which Digital Skills and Learning Motivation influence the strength of the relationship between the other variables in the model, signifying that the impact of independent variables on dependent variables fluctuates based on the level of the moderator variable [49].

The structural route indicates that Social Support affects Digital Learning Interaction, while Digital Skills and Learning Motivation impact E-Learning Usage Patterns [50]. These two mediating factors influence Critical Thinking Development and Digital Behavior Transformation, hence enhancing Continuous Learning Outcomes. The model illustrates that the efficacy of e-learning necessitates a comprehensive strategy that enhances the intricate connections of social, technical, and motivational elements inside the digital learning environment [51].

Line Notation Explanation:

1) The solid line (—) indicates a direct relationship hypothesized based on the theory, reflecting the main causal path in the structural model.
2) The dotted line (- -) indicates the moderating relationship, where Digital Skills and Learning Motivation moderate the strength of the relationship between the other variables in the model.

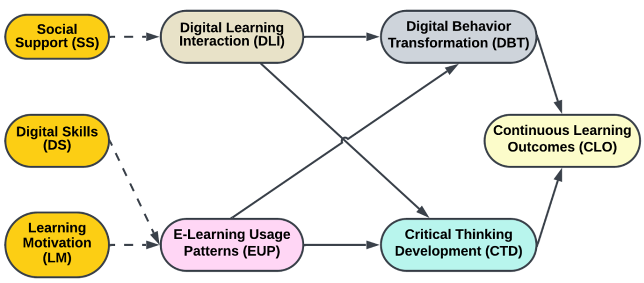

Fig 1. Conceptual framework.

F. *Ethical Considerations*

This study was conducted in full compliance with recognized ethical standards for educational research, adhering to the seven WHO 2011 Standards and the 2016 CIOMS Guidelines. The research protocol received ethical approval from the Research Ethics Committee of Universitas Negeri Padang (KOMITE ETIK PENELITIAN) with Ethical Exemption Certificate No. 020/KEPK-UNP/7/2025, dated July 25, 2025, valid until July 25, 2026. The ethical review confirmed that the study met all seven WHO standards: (1) Social Values, (2) Scientific Values, (3) Equitable Assessment and Benefits, (4) Risks, (5) Persuasion/Exploitation, (6) Confidentiality and Privacy, and (7) Informed Consent. Prior to data collection, comprehensive institutional approval was secured from all collaborating institutions, and written informed consent was obtained from each participant. Participants were thoroughly informed about the research objectives, procedures, and their rights, including voluntary participation and the freedom to withdraw at any time without academic consequences. Special attention was given to ensuring that participation or non-participation would not affect students' academic standing or relationships with instructors.

The study implemented stringent measures to protect participant confidentiality and data security throughout the research process. All collected data were anonymized using unique identification codes, with personal identifying information removed from datasets prior to analysis. Survey responses and longitudinal data were encrypted and stored on secure institutional servers accessible only to authorized research team members who had signed confidentiality agreements. To ensure participant welfare during the longitudinal study period, regular check-ins were conducted to assess any concerns, and support mechanisms were established to address technical issues or psychological stress related to participation. Upon completion of the study, all participants received a comprehensive summary report of the research findings, acknowledging their valuable contribution to advancing understanding of e-learning effectiveness in vocational education. The research team remains committed to maintaining the highest ethical standards in disseminating results, ensuring accurate and transparent reporting while protecting the identity and dignity of all participants.

IV. Result and Discussion

A. *Research Results*

1) *Evaluation of measurement models*

Prior to testing the structural hypothesis, this research first conducts a thorough evaluation of the measurement model to ascertain the validity and reliability of all the constructs used. First, the measurement model was evaluated to confirm construct validity and reliability. All indicators showed strong loadings (0.788–0.897), exceeding the threshold of 0.7. Table 2 presents these results. Fig. 2 and Table 2 provide the detailed results of the evaluation of this measurement model.

Fig. 2 illustrates the output findings of PLS-SEM, presenting a comprehensive structural model that encompasses all interactions among components. This model illustrates the proposed association among EUP, DLI, CTD, DBT, and CLO, including the moderating variables LM, DS, and SS. Fig. 2 presents an in-depth depiction of the intricacy of the linkages examined in this longitudinal research, illustrating the route coefficients and significant levels of each relationship within the structural model. Table 2 displays the comprehensive findings of the assessment of this measuring model [52].

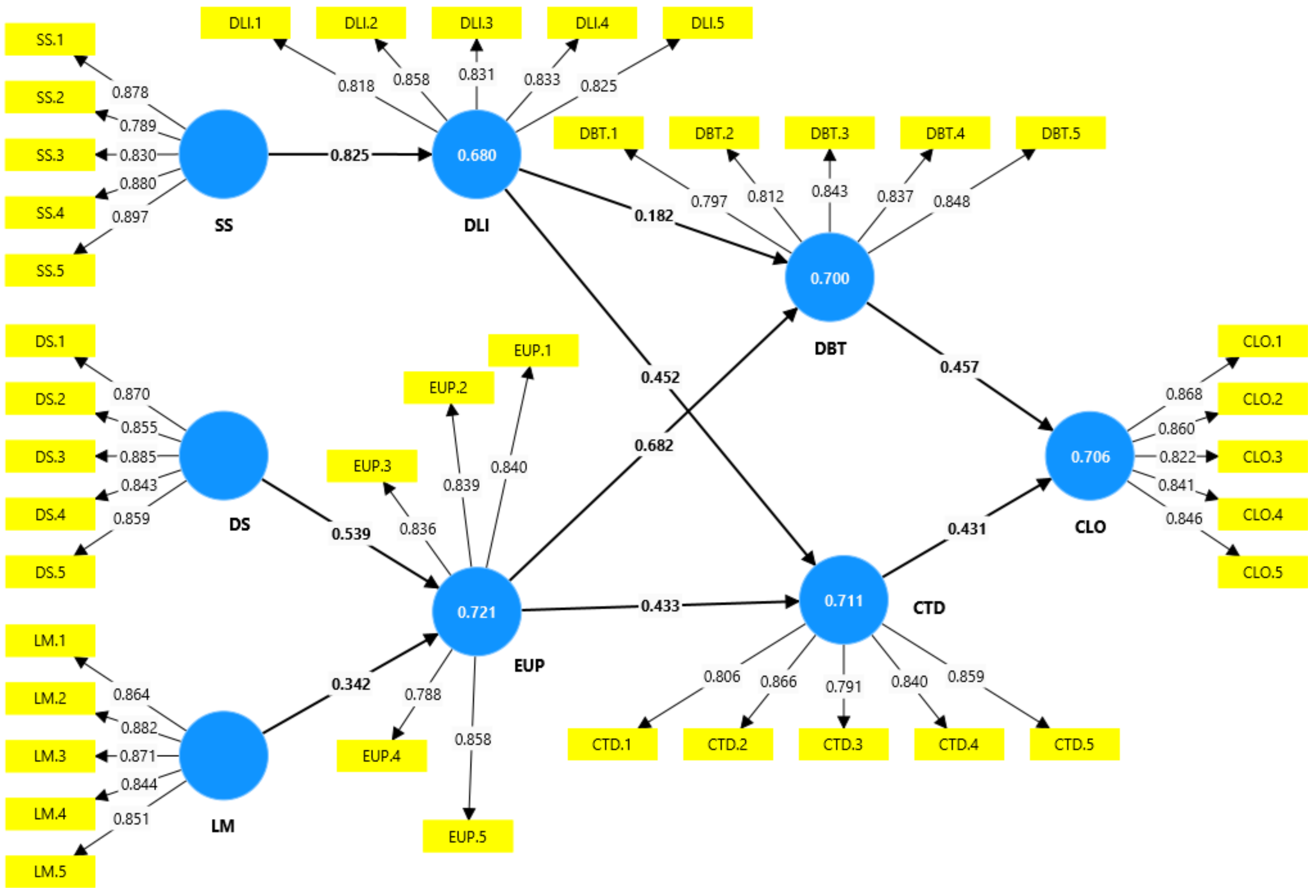

Fig. 2. PLS-SEM output.

Table 3 delineates the comprehensive outcomes of the measurement model assessment, including outer loading, VIF, Cronbach's alpha, composite reliability, and Average Variance Extracted (AVE) for all study topics. The assessment outcomes in Table 2 indicate that all constructs satisfy the necessary standards of validity and reliability. All indicators have outer loadings exceeding the minimal criterion of 0.7, with values ranging from 0.788 to 0.897, indicating that each indicator effectively captures its underlying variables. The VIF values for all indices were below 5.0, indicating the absence of significant multicollinearity issues. Cronbach's alpha for all structures was above 0.885, indicating exceptional internal consistency. The composite reliability ranges from 0.916 to 0.936, significantly above the 0.7 threshold, thereby affirming the construct's strong dependability. The Average Variance Extracted (AVE) for all constructs exceeds 0.5, with the most outstanding value in Digital Skills (0.744) and the lowest in Digital Behavior Transformation (0.685), demonstrating sufficient convergent validity as shown in Table 2.

2) Evaluation of discriminatory validity

Discriminant validity is crucial for confirming that each concept inside the model is distinct and separate. The assessment was conducted using two primary methodologies: the Fornell-Larcker criteria and the Heterotrait-Monotrait ratio (HTMT). Table 3 presents the comprehensive findings of the discriminant validity assessment using both methodologies [53].

Table 3. Measurement model evaluation: factor loading, reliability, and convergent validity

Constructs	Outer Loading		VIF	Cronbach's alpha	Composite reliability	(AVE)
CLO	CLO.1	0.868	2.597	0.902	0.927	0.718
	CLO.2	0.860	2.565			
	CLO.3	0.822	2.100			
	CLO.4	0.841	2.353			
	CLO.5	0.846	2.409			
CTD	CTD.1	0.806	2.132	0.889	0.919	0.694
	CTD.2	0.866	2.694			
	CTD.3	0.791	1.943			
	CTD.4	0.840	2.219			
	CTD.5	0.859	2.463			
DBT	DBT.1	0.797	1.935	0.885	0.916	0.685

Constructs	Outer Loading		VIF	Cronbach's alpha	Composite reliability	(AVE)
	DBT.2	0.812	1.932			
	DBT.3	0.843	2.238			
	DBT.4	0.837	2.231			
	DBT.5	0.848	2.311			
DLI	DLI.1	0.818	2.040	0.890	0.919	0.694
	DLI.2	0.858	2.486			
	DLI.3	0.831	2.136			
	DLI.4	0.833	2.214			
	DLI.5	0.825	2.075			
DS	DS.1	0.870	2.796	0.914	0.936	0.744
	DS.2	0.855	2.622			
	DS.3	0.885	3.027			
	DS.4	0.843	2.295			
	DS.5	0.859	2.716			
EUP	EUP.1	0.840	2.234	0.889	0.919	0.693
	EUP.2	0.839	2.186			
	EUP.3	0.836	2.226			
	EUP.4	0.788	1.916			
	EUP.5	0.858	2.396			
LM	LM.1	0.864	2.748	0.914	0.936	0.744
	LM.2	0.882	2.882			
	LM.3	0.871	2.826			
	LM.4	0.844	2.371			
	LM.5	0.851	2.362			
SS	SS.1	0.878	2.987	0.908	0.932	0.732
	SS.2	0.789	1.934			
	SS.3	0.830	2.327			
	SS.4	0.880	2.881			
	SS.5	0.897	3.628			

Table 4. Discriminant validity

Constructs		Constructs							
		I	II	III	IV	V	VI	VII	VIII
I	CLO	**0.848**	0.881	0.890	0.942	0.964	0.931	0.957	0.908
II	CTD	0.793	**0.833**	0.889	0.902	0.875	0.894	0.891	0.824
III	DBT	0.798	0.791	**0.828**	0.828	0.879	0.932	0.853	0.843
IV	DLI	0.846	0.805	0.738	**0.833**	0.917	0.915	0.931	0.915
V	DS	0.875	0.792	0.792	0.827	**0.862**	0.918	0.933	0.930
VI	EUP	0.838	0.802	0.830	0.815	0.830	**0.833**	0.886	0.844
VII	LM	0.869	0.805	0.770	0.840	0.852	0.801	**0.863**	0.894
VIII	SS	0.824	0.745	0.758	0.825	0.848	0.762	0.817	**0.856**

Note: HTMT ratio is shown above the diagonal (in italics). At the same time, the Fornell-Larcker criteria is represented by the square root of the AVE along the diagonal (in bold), with construct correlations displayed below the diagonal.

Table 4 displays a discriminant validity matrix that combines the results of the Fornell-Larcker criterion (the square root of AVE on the diagonal and the correlations between components below the diagonal) with the HTMT ratio (above the diagonal). The assessment findings, as shown in Table 3, indicate satisfactory performance, albeit with some critical observations. According to the Fornell-Larcker criteria, the square root of the Average Variance Extracted (AVE) on the diagonal (bold) for all constructs exceeds the correlations between constructs below the diagonal, demonstrating the technical validity of the discriminant. The examination of the HTMT ratio above the diagonal reveals several values approaching or marginally exceeding the conservative threshold of 0.85, particularly in the associations between Digital Skills and Continuous Learning Outcomes (0.964), Digital Learning Interaction and Learning Motivation (0.931), and various other construct pairs. Nonetheless, the majority of the HTMT values in Table 3 remain within the allowed limits, and the strong association across constructs may be interpreted within the framework of e-learning research, where the variables are conceptually interconnected.

3) Structural model evaluation

Following the assessment of the measurement model's quality, the analysis proceeds to evaluate the structural model, examining the robustness of the relationships between the constructs and the model's predictive capability. Tables 5 and 6 present the outcomes of the structural model assessment, including the R^2, modified R^2, and effect size (f^2) for all relationships within the model [54].

Table 5. Model predictive capability (R^2 values)

Constructs	R^2	R^2 adjusted
CLO	0.706	0.703
CTD	0.711	0.708
DBT	0.700	0.698
DLI	0.680	0.679
EUP	0.721	0.719

Table 6. Path relationship effect sizes (f^2)

Path Relationships	f^2
CTD → CLO	0.236
DBT → CLO	0.265
DLI → CTD	0.237
DLI → DBT	0.037
DS → EUP	0.286
EUP → CTD	0.218
EUP → DBT	0.520
LM → EUP	0.115
SS → DLI	2.127

Tables 5 and 6 present the outcomes of the structural model assessment, including the R^2 value and effect size (f^2) to evaluate the predictive capability and impact across constructs. The evaluation results consistently shown strong predictive capability for all endogenous variables, with R^2 values between 0.680 and 0.721, indicating that the model explained over 68% of the variation in each outcome construct.

E-learning usage Patterns had the best predictive capacity (R^2 = 0.721), while Digital Learning Interaction demonstrated the lowest, although still significant, value (R^2 = 0.680). The distinctive results indicate that Social Support exerts a substantial impact size on Digital Learning Interaction (f^2 = 2.127), significantly surpassing other associations and affirming the preeminent function of social support in digital learning. Conversely, Digital Learning Interaction, compared to Digital Behavior Transformation, had a minimal impact size (f^2 = 0.037), indicating a diminished route of influence.

The assessment findings generally affirmed that structural models had strong predictive capacities, with impact sizes ranging from tiny to extremely high, indicating that the various paths in the model exert differing amounts of influence. All continue to make substantial contributions to digital learning outcomes.

4) Model conformity evaluation

The model fit assessment is carried out to evaluate how well the proposed theoretical model is by the empirical data collected. Table 7 presents various model fit indicators to assess the model's overall quality [55].

Table 7. Model fit

Indicators	Saturated model	Estimated model
SRMR	0.048	0.103
d_ULS	1.909	8.721
d_G	1.362	1.747
Chi-square	1626.324	1809.110
NFI	0.815	0.794

5) Model conformity evaluation

Table 6 presents model suitability indicators that compare saturated and estimated models across five evaluation criteria. The results showed mixed performance, with the SRMR saturated model showing the best value (0.048) in the excellent category, while the estimated model remained within acceptable limits (0.103). The NFI values for both models were above the minimum threshold but did not reach the ideal level, with the saturated model slightly superior (0.815 vs 0.794).

The distinctive results reveal significant disparities between the saturated and estimated models across several indicators, particularly d_ULS, which demonstrates significant discrepancies (1,909 vs. 8,721), highlighting the intricate nature of the connections among variables that the theoretical model fails to completely encompass. Although the model did not attain a perfect match, the attained fit was sufficient for interpretation and deriving relevant study results.

An exhaustive assessment of the measurement and structural models illustrated in Fig. 2, Tables 2–6 indicates that the research model possesses satisfactory psychometric properties and significant predictive capability, thereby establishing a robust foundation for result interpretation and hypothesis testing regarding the ongoing influence of e-learning integration on automotive engineering students.

6) Hypothesis testing through bootstrapping analysis

After evaluating the measurement and structural models demonstrated adequate psychometric quality, the analysis was followed by hypothesis testing using a bootstrapping procedure to test the statistical significance of the entire relationship in the structural model. Fig. 3 shows a bootstrapping output that provides a comprehensive visualization of the importance of each path in the model, while Tables 7–9 present detailed results from the analysis of direct effects, specific indirect effects, and total effects.

7) Direct effect analysis

The findings from the direct effects analysis in Table 8 indicate that all hypotheses posited in this research are statistically significant. The correlation between Social Support and Digital Learning Interaction was robust, shown by a path coefficient of 0.825 (t-statistic = 25.151, $p < 0.001$), affirming the essential importance of social support in fostering students' active engagement in digital learning interactions. The analysis of e-learning usage patterns on digital behavior transformation revealed a path coefficient of 0.682 (t-statistic = 9.275, $p < 0.001$), demonstrating that intensive e-learning usage patterns substantially altered students' digital behavior. The correlation between digital skills and e-learning use patterns was quantified at 0.539 (t-statistic = 8.079, $p < 0.001$), indicating that proficient digital abilities are a significant predictor of successful e-learning platform utilization.

Table 8. Direct effect

Path Relationships	Original sample	Sample mean	Standard deviation	T statistics	*P* values
CTD → CLO	0.431	0.431	0.076	5.647	0.000
DBT → CLO	0.457	0.457	0.087	5.245	0.000
DLI → CTD	0.452	0.454	0.068	6.639	0.000
DLI → DBT	0.182	0.181	0.084	2.161	0.015
DS → EUP	0.539	0.537	0.067	8.079	0.000
EUP → CTD	0.433	0.431	0.075	5.756	0.000
EUP → DBT	0.682	0.681	0.074	9.275	0.000
LM → EUP	0.342	0.343	0.065	5.217	0.000
SS → DLI	0.825	0.824	0.033	25.151	0.000

The results of the direct effects analysis in Table 7 confirm all hypotheses with consistent statistical significance ($p < 0.05$). Social Support showed a remarkable dominance of Digital Learning Interaction with the strongest coefficient ($\beta = 0.825$, t-statistic = 25.151), indicating that social Support is a major driver in the digital learning ecosystem. E-learning usage Patterns also substantially influenced Digital Behavior Transformation (β = 0.682, t-statistic = 9.275), confirming the transformative role of e-learning usage patterns.

The interesting findings show a nearly equal contribution between Critical Thinking Development (β = 0.431) and Digital Behavior Transformation (β = 0.457) to Continuous

Learning Outcomes, indicating that both aspects of student development are equally important for continuous learning outcomes. Digital Learning Interaction versus Digital Behavior Transformation showed the most negligible direct effect (β = 0.182, p = 0.015), although it remained statistically significant. Overall, the varying strength of relationships provides essential insights into the priorities of interventions in developing effective e-learning systems.

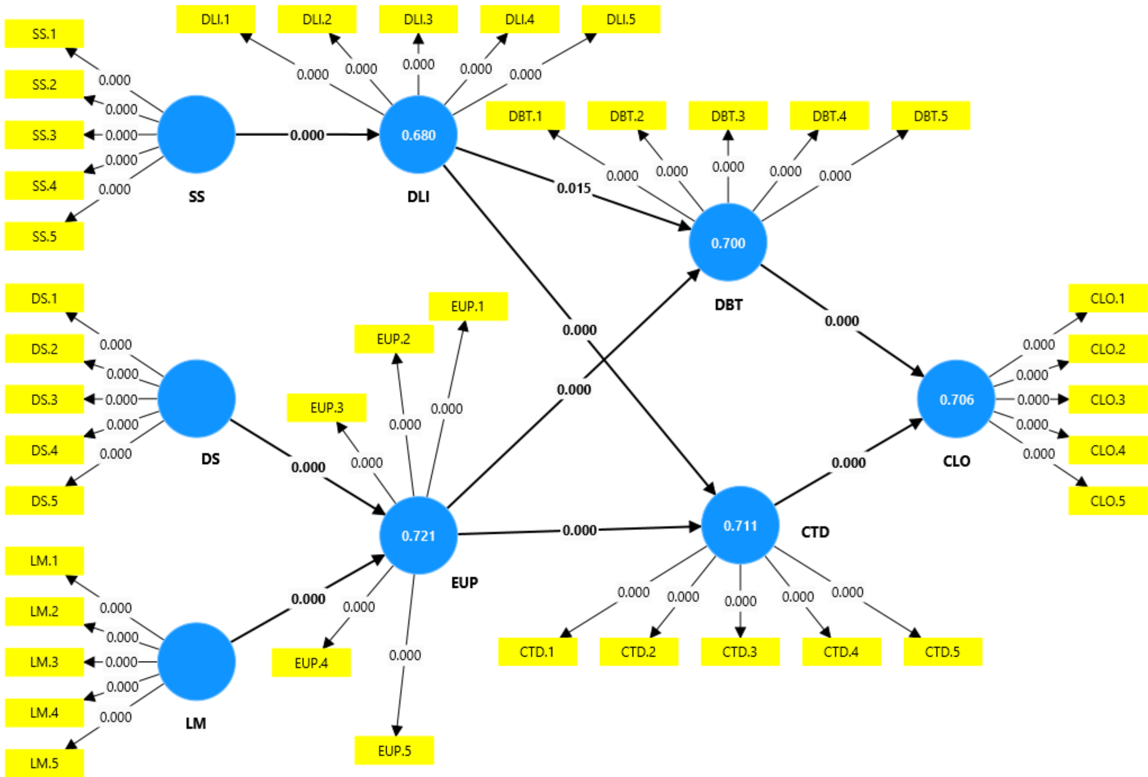

Fig. 3. Bootsraping output.

8) Analysis of specific indirect effects

Table 8 presents the results of the mediation effect analysis that provides in-depth insights into the complex mechanisms of how the variables in the model affect each other through indirect pathways. Digital Skills showed a strong indirect effect on Digital Behavior Transformation through E-Learning Usage Patterns with a coefficient of 0.368 (t-statistic = 6.109, p < 0.001), confirming the significant mediating role of e-learning usage patterns in linking digital skills with digital behavior transformation. Social Support showed a substantial indirect effect on Critical Thinking Development through Digital Learning Interaction with a coefficient of 0.373 (t-statistic = 6.331, p < 0.001), suggesting that social Support contributes to developing critical thinking through increased digital learning interactions.

Table 9 reveals a complex mediation mechanism with all indirect effect pathways proven statistically significant. Social Support showed the most substantial indirect effect through Digital Learning Interaction on Critical Thinking Development (β = 0.373, t-statistic = 6.331), confirming the fundamental role of social Support in developing students' critical thinking skills through increased digital learning interaction. Digital Skills also substantially indirectly affected Digital Behavior Transformation through E-Learning Usage Patterns (β = 0.368, t-statistic = 6.109). This shows that technology competencies translate into digital behavior transformation through platform usage optimization.

Table 9. Specific indirect effect

Path Relationships	Original sample	Sample mean	Standard deviation	T statistics	*P* values
DLI → DBT → CLO	0.083	0.086	0.047	1.750	0.040
DS → EUP → DBT	0.368	0.366	0.060	6.109	0.000
DLI → CTD → CLO	0.195	0.195	0.042	4.648	0.000
LM → EUP → CTD	0.148	0.147	0.037	3.956	0.000
EUP → DBT → CLO	0.312	0.309	0.061	5.149	0.000
LM → EUP → DBT	0.233	0.234	0.054	4.298	0.000
EUP → CTD → CLO	0.187	0.187	0.052	3.626	0.000
SS → DLI → CTD	0.373	0.375	0.059	6.331	0.000
SS → DLI → DBT	0.150	0.150	0.070	2.138	0.016
SS → DLI → DBT → CLO	0.068	0.071	0.040	1.727	0.042
SS → DLI → CTD → CLO	0.161	0.161	0.035	4.539	0.000
DS → EUP → CTD → CLO	0.101	0.101	0.032	3.175	0.001
LM → EUP → DBT → CLO	0.106	0.107	0.031	3.412	0.000
DS → EUP → DBT → CLO	0.168	0.166	0.039	4.308	0.000
LM → EUP → CTD → CLO	0.064	0.064	0.021	3.067	0.001
DS → EUP → CTD	0.234	0.232	0.052	4.458	0.000

Interesting findings show the existence of a significant dual mediating pathway, where antecedent variables can influence outcomes through multiple pathways. E-learning usage Patterns function as a key mediator with a strong indirect effect on Continuous Learning Outcomes through Digital Behavior Transformation (β = 0.312) and Critical Thinking Development (β = 0.187). The most negligible indirect effect was found on the Learning Motivation pathway on Continuous Learning Outcomes through Critical Thinking Development (β = 0.064), although it remained significant. Overall, the complexity of this mediation pathway confirms that the benefits of e-learning are achieved through a gradual process involving multiple mechanisms rather than through direct effects alone.

9) Total effect analysis

Table 10 presents the total effect results that combine direct and indirect effects, providing a comprehensive overview of the total influence of each variable on the other variables in the model. Social Support showed the most substantial total effect on Digital Learning Interaction (coefficient = 0.825, t-statistic = 25.151, p < 0.001), confirming its critical role in the digital learning ecosystem. E-Learning Usage Patterns showed a strong total effect on Digital Behavior Transformation (coefficient = 0.682, t-statistic = 9.275, p < 0.001) and Continuous Learning Outcomes (coefficient = 0.498, t-statistic = 8.962, p < 0.001), suggesting that e-learning usage patterns are the main drivers for digital behavior transformation and continuous learning outcomes.

Table 10. Total effect

Path Relationships	Original sample	Sample mean	Standard deviation (STDEV)	T statistics	*P* values
CTD → CLO	0.431	0.431	0.076	5.647	0.000
DBT → CLO	0.457	0.457	0.087	5.245	0.000
DLI → CLO	0.278	0.281	0.052	5.336	0.000
DLI → CTD	0.452	0.454	0.068	6.639	0.000
DLI → DBT	0.182	0.181	0.084	2.161	0.015
DS → CLO	0.269	0.267	0.047	5.720	0.000
DS → CTD	0.234	0.232	0.052	4.458	0.000
DS → DBT	0.368	0.366	0.060	6.109	0.000
DS → EUP	0.539	0.537	0.067	8.079	0.000
EUP → CLO	0.498	0.496	0.056	8.962	0.000
EUP → CTD	0.433	0.431	0.075	5.756	0.000
EUP → DBT	0.682	0.681	0.074	9.275	0.000
LM → CLO	0.170	0.170	0.039	4.362	0.000
LM → CTD	0.148	0.147	0.037	3.956	0.000
LM → DBT	0.233	0.234	0.054	4.298	0.000
LM → EUP	0.342	0.343	0.065	5.217	0.000
SS → CLO	0.229	0.232	0.045	5.088	0.000
SS → CTD	0.373	0.375	0.059	6.331	0.000
SS → DBT	0.150	0.150	0.070	2.138	0.016
SS → DLI	0.825	0.824	0.033	25.151	0.000

Table 10 shows the accumulation of direct and indirect effects that confirm the overall predictive power of the model with all statistically significant relationships. Social Support remained dominant with the most substantial impact on Digital Learning Interaction (β = 0.825, t-statistic = 25.151). At the same time, E-Learning Usage Patterns emerged as the key driver with a substantial total effect on all primary outcomes, particularly Digital Behavior Transformation (β = 0.682) and Continuous Learning Outcomes (β = 0.498).

Significant findings suggest that antecedent variables have a wide range of influence. For example, Digital Skills showed the most substantial effect on E-Learning Usage Patterns (β = 0.539), and Social Support substantially impactedritical Thinking Development (β = 0.373). In contrast, Learning Motivation showed a consistent but moderate effect across all outcomes. Overall, the total impact confirms that each component in the model contributes significantly to digital learning transformation, with Social Support and E-Learning Usage Patterns as the main leverage points in the e-learning ecosystem.

10) Findings bootstrapping synthesis

The bootstrapping analysis findings unequivocally validate all hypotheses posited in this work, demonstrating a constant degree of significance across all routes in the structural model. The results indicate that the theoretical model established has robust empirical Support and may elucidate the intricate interactions among variables within the framework of e-learning integration.

The differing impact of effects along paths offers critical insights into the prioritization of interventions for developing successful e-learning systems. Social Support is the predominant component influencing Digital Learning Interaction, although Digital Skills and Learning Motivation are essential drivers of good E-Learning Usage Patterns. The substantial mediating impact illustrates the intricate processes via which antecedent factors progressively influence results, affirming the need for a comprehensive strategy in the implementation of e-learning that takes into account the complete digital learning environment.

B. Interpretation of PLS Predict Analysis and Cross-Validated Predictive Ability Test (CVPAT)

1) Evaluation of model predictive power via PLS predict

Following the validation of all relationships in the structural model using bootstrapping analysis, the assessment continued with an examination of the model's predictive capability utilizing the PLS Predict technique and the Cross-Validated Predictive Ability Test (CVPAT). This study is essential for assessing the model's capacity to forecast fresh data and for validating its predictive efficacy beyond the sample used in the estimations [56, 57].

2) PLS predict analysis

Table 11 displays the results from the PLS Predict study, which evaluates the predictive efficacy of the PLS-SEM model against the Linear Model (LM) as a reference point. The assessment comprises three primary metrics: Q²predict as a measure of predictive capability, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) to evaluate prediction accuracy at the indicator level [56].

Table 11 illustrates the predictive performance, with Q²predict values that range from 0.352 to 0.558 across all variables. Continuous Learning Outcomes had the strongest and most consistent predictive performance (Q²predict 0.494–0.558), with CLO.1 attaining the peak value (0.558). Conversely, Critical Thinking Development had the most variety, with CTD.3 recording the lowest score in the whole model (0.352), but CTD.5 demonstrated commendable performance (0.534).

Table 11. PLS predict

Constructs	Q²predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
CLO.1	0.558	0.576	0.437	0.577	0.420
CLO.2	0.544	0.609	0.490	0.594	0.436
CLO.3	0.494	0.639	0.488	0.638	0.470
CLO.4	0.516	0.624	0.493	0.593	0.438
CLO.5	0.535	0.591	0.486	0.567	0.428
CTD.1	0.394	0.710	0.510	0.751	0.534
CTD.2	0.497	0.628	0.479	0.647	0.480
CTD.3	0.352	0.701	0.512	0.728	0.531
CTD.4	0.454	0.680	0.538	0.669	0.521
CTD.5	0.534	0.627	0.490	0.645	0.489
DBT.1	0.353	0.693	0.540	0.723	0.557
DBT.2	0.507	0.613	0.482	0.644	0.479
DBT.3	0.458	0.625	0.498	0.653	0.505
DBT.4	0.413	0.676	0.536	0.700	0.544
DBT.5	0.486	0.653	0.506	0.676	0.501
DLI.1	0.481	0.662	0.511	0.650	0.502
DLI.2	0.443	0.731	0.539	0.729	0.533
DLI.3	0.462	0.677	0.486	0.658	0.474
DLI.4	0.454	0.676	0.485	0.671	0.477
DLI.5	0.490	0.629	0.483	0.577	0.421
EUP.1	0.502	0.641	0.506	0.669	0.518
EUP.2	0.550	0.620	0.463	0.654	0.483
EUP.3	0.444	0.632	0.498	0.650	0.506
EUP.4	0.416	0.662	0.506	0.709	0.537
EUP.5	0.551	0.594	0.458	0.622	0.479

Comparisons with linear benchmark models demonstrate the superiority of the PLS-SEM model, particularly in terms of MAE measures, where the PLS-SEM model consistently outperforms the linear model across most indices. Despite the RMSE performance yielding inconsistent outcomes, the PLS-SEM model exhibited predictive skills that were either superior to or equivalent to the benchmark, affirming that the model not only statistically fits but also has practical predictive usefulness for e-learning applications.

3) Cross-Validated Predictive Ability Test (CVPAT)

Table 12 presents the results of the Cross-Validated Predictive Ability Test, which provides a formal statistical assessment of the predictive superiority of the PLS-SEM model in comparison to the Information Approach (IA) as a simplistic benchmark. The CVPAT study employed a cross-validation method to assess the disparity in loss functions between the PLS-SEM model and the benchmark, using a t-test to evaluate statistical significance [57].

Table 12. Cross-validated predictive ability test comparing PLS-SEM and information approach models

Constructs	PLS loss	IA loss	Average loss difference	t value	p value
CLO	0.370	0.785	−0.415	6.323	0.000
CTD	0.449	0.813	−0.364	5.741	0.000
DBT	0.426	0.767	−0.340	4.865	0.000
DLI	0.457	0.854	−0.397	5.144	0.000
EUP	0.397	0.786	−0.389	4.976	0.000
Overall	0.420	0.801	−0.381	5.715	0.000

Table 12 shows the PLS-SEM model's consistent and significant predictive superiority over the Information Approach benchmark across all endogenous constructs. Continuous Learning Outcomes showed the best performance with the most essential average loss difference (−0.415, t-value = 6.323, $p < 0.001$), while Digital Behavior Transformation had the most minor but still substantial difference (−0.340, t-value = 4.865, $p < 0.001$). The PLS-SEM model consistently outperformed the benchmark by a significant margin across all variables.

The comprehensive assessment validated the model's superiority, as evidenced by an average loss difference of −0.381 (t-value = 5.715, $p < 0.001$), providing robust statistical confirmation that the constructed PLS-SEM model had enhanced predictive capabilities relative to the naïve method. The CVPAT findings validate that the model is statistically robust and has significant and dependable prediction capability for the actual implementation of evidence-based e-learning systems.

4) Implications of predictive analysis for model validity

The results of the PLS Predict, and CVPAT analyzes provide strong empirical validation of the model's predictive capabilities developed in this study. Consistently superior predictive performance compared to benchmark models indicates that structural models capture statistically significant relationships and have practical predictive utility. The variability in Q²predict across indicators provides insight into the relative strength of various aspects in each construct, with some indicators showing higher predictive capabilities than others.

The consistent superiority in CVPAT across all endogenous constructs confirms that the developed theoretical model has a reliable predictive advantage. The high t-statistical values and significant p-values indicate that this superiority is not the result of random sampling variation but reflects the inherent strength of the structural model. These results strengthen confidence in the research findings and provide empirical support for the practical application of the model in the context of the development and implementation of e-learning systems.

5) Predictive power evaluation synthesis

Comprehensive evaluation through PLS Predict and CVPAT showed that the research model met the statistical fit criteria and demonstrated superior predictive capabilities. Combining positive Q^2predict, competitive or superior RMSE and MAE performance, and statistically significant CVPAT results provides multi-dimensional model quality and utility validation. These findings indicate that the model can be used to understand the relationships between variables in the context of the research sample and to predict outcomes in the broader population, providing a solid basis for the generalization of findings and practical application in developing effective e-learning strategies.

C. Discussion

1) Interpretation of key findings in a theoretical context

The empirical evidence reveals that e-learning's impact extends beyond immediate academic gains to fundamental behavioral transformations. The strong relationship between E-Learning Usage Patterns and Digital Behavior Transformation ($\beta = 0.682$) indicates that sustained platform engagement creates lasting changes in how students interact with digital technologies—a critical competency for Industry 4.0 readiness. [15, 18].

2) The significance of the mediation effect in the digital learning ecosystem

The examination of indirect effects uncovers intricate and significant mediation processes within this research paradigm. Digital Learning Interaction serves as a crucial mediator connecting e-learning use patterns to the enhancement of critical thinking abilities ($\beta = 0.195$, $p < 0.001$). The results indicate that the advantages of e-learning in developing analytical abilities do not arise just from technological exposure; instead, they need active and collaborative engagement within a digital learning environment.

The mediating role of E-Learning Usage Patterns in connecting Digital Skills with various learning outcomes confirms the importance of basic digital skills as a foundation for the effective use of e-learning platforms. The indirect effect of Digital Skills on Digital Behavior Transformation through E-Learning Usage Patterns ($\beta = 0.368$, $p < 0.001$) shows that students with strong digital skills can better optimize the use of e-learning platforms, accelerating their digital behavior transformation. These findings are essential for students' onboarding strategies and digital capacity building in vocational education programs.

A dual mediation pathway, including Learning Motivation, illustrates how students' intrinsic motivation can be converted into tangible learning results through enhanced e-learning and skill acquisition. The indirect effects of Learning Motivation on Continuous Learning Outcomes via Digital Behavior Transformation ($\beta = 0.106$, $p < 0.001$) and Critical Thinking Development ($\beta = 0.064$, $p = 0.001$) indicate that elevated learning motivation fosters a positive cycle that enhances the benefits of continuous learning [58].

3) Implications for the design and implementation of e-learning in vocational education

The results of this study provide significant practical insights for the development and implementation of efficient e-learning systems in vocational education. The pre-eminence of Social Support as a determinant of Digital Learning Interaction underscores the need for educational institutions to invest in establishing a robust social support framework. This includes educating teachers to enable digital learning, establish peer mentoring systems, and devise communication platforms that foster cooperation and social engagement in a virtual setting.

The correlation between Digital Skills and E-Learning Usage Patterns ($\beta = 0.539$, $p < 0.001$) underscores the need for a structured digital literacy development initiative as a requirement for effective e-learning execution. Vocational education institutions must develop a cohesive digital literacy curriculum that imparts technical skills while enhancing students' confidence and self-efficacy in technology learning. Thorough onboarding programs and continuous technical assistance are essential elements for successful e-learning implementation.

The relevance of Learning Motivation in shaping e-learning use patterns underscores the need for a cohesive, motivating approach in the creation of digital learning platforms. Elements such as gamification, individualized learning trajectories, immediate feedback, and acknowledgment systems may enhance students' intrinsic motivation and foster more engagement with educational content. In vocational education, a definitive link between e-learning material and practical applications, as well as industrial relevance, is essential for sustaining student interest in learning [59].

4) Contributions to digital learning theory and behavioral transformation

This research makes a significant theoretical contribution by integrating longitudinal perspectives in understanding the impact of e-learning. The developed model demonstrates that the benefits of e-learning are not limited to short-term improvements in academic performance but include fundamental transformations in how students process information, interact with technology, and develop sustainable learning capacity. Conceptualization of Digital Behavior Transformation as a separate outcome but related to Critical Thinking Development provides important theoretical nuances in understanding the impact of multidimensional e-learning.

The finding that Critical Thinking Development and Digital Behavior Transformation contribute almost equally to Continuous Learning Outcomes ($\beta = 0.431$ and $\beta = 0.457$, respectively) confirms the importance of a holistic approach in student development. This shows that educational institutions need to develop strategies that focus on improving analytical skills and transforming digital behaviors that support lifelong learning.

This study model advances mediation theory within digital learning by demonstrating how Digital Learning Interaction serves as a crucial mechanism that transforms technology use into cognitive skill development. These findings enrich a theoretical understanding of the conditions and processes required to achieve optimal learning benefits from educational technology investments [60].

5) Comparison with previous research and position in the literature

The findings of this study build upon and expand upon prior studies in numerous significant respects. The results of Wagino *et al.* [10] regarding the efficacy of e-learning in technical education are corroborated by empirical data that detail the exact processes underlying these beneficial effects. The research indicates that the advantages of e-learning extend beyond the mere acquisition of theoretical information to include the alteration of digital behavior, which has enduring effects on professional growth.

This research provides a more comprehensive view than studies using the DeLone & McLean Model for e-learning assessment, as it incorporates social and motivational variables that are sometimes overlooked in the technical evaluation framework. The focus on Social Support as a crucial factor addresses deficiencies in the literature that prioritise technical and systemic elements while neglecting the human component of e-learning implementation.

This research's distinctive addition is its longitudinal strategy, which facilitates an understanding of the evolution and persistence of e-learning advantages over time. The majority of research in this domain is cross-sectional, emphasizing short-term effects. This research demonstrates that investments in e-learning yield lasting benefits by enhancing self-learning capabilities and facilitating digital behavioral change [61].

6) Implications for education policy and curriculum development

The findings of this study have significant policy implications for the development of vocational education in the digital era. The predictive power of the model (R-square > 0.68 for all endogenous constructs) provides a solid empirical basis for the justification of institutional investment in e-learning infrastructure and digital capacity building. Policymakers need to consider the technological aspects and the investments in human resource development, support systems, and organizational culture changes necessary to achieve the optimal benefits of digitalizing education.

The significance of Social Support in the model shows the need for policies that support the development of digital learning communities. This includes allocating resources for faculty development training, developing peer support systems, and creating incentives for active participation in the digital learning ecosystem. Institutions need to build a comprehensive change management strategy recognizing that digital transformation in education is a socio-technical process requiring changes in pedagogical practices, organizational structures, and academic culture.

From the curriculum development perspective, this study emphasizes the need for systematic integration between digital literacy development, critical thinking skills, and technical competence. Vocational education programs must adopt an approach that integrates digital learning not as an add-on but as an integral component of the student learning experience. This requires a curriculum redesign that optimizes the synergy between online and offline learning, focusing on developing skills relevant to the Industry 4.0 era [62].

7) Validity and reliability of findings in the context of vocational education

The study's outcomes were substantiated by an extensive analysis including construct validity, reliability, and the model's predictive efficacy. The high composite reliability value (>0.916) and the acceptable Average Variance Extracted (>0.685) for all constructs indicate that the research instrument effectively evaluates the phenomena in question. The consistency of results across many evaluation criteria (Cronbach's alpha, composite reliability, AVE) instills significant trust in the internal validity of the findings.

The persistent dominance of the PLS-SEM model over the benchmark models in the CVPAT study (average loss difference = −0.381, $p < 0.001$) indicates that the model is both statistically robust and practically predictive. This suggests that the model can forecast results in like situations and establishes a robust foundation for extrapolating findings to a broader demographic of vocational education students.

The study's external validity was enhanced by stratified random sampling, accounting for differences in e-learning experiences across student cohorts. The sample's representativeness across different degrees of exposure to digital learning technologies enhances confidence in the generalisability of the results within vocational education. Nonetheless, it must be acknowledged that the particularity of the automotive engineering environment may restrict the applicability of results to other vocational fields [63].

8) Research limitations and future development directions

While this study offers a substantial contribution, several limitations must be acknowledged in the interpretation and application of the results. Dependence on self-report instruments may generate biases that compromise data integrity. The construct's strong validity indicates that such bias does not significantly undermine the validity of the results. Subsequent studies may address these constraints by incorporating objective metrics, such as learning analytics data, e-learning activity log files, and quantifiable performance indicators.

Longitudinal time spans from baseline to twelve months post-implementation, with three data collection points, although significant for educational research, may be inadequate to fully capture the long-term consequences of digital behavioral change. A subsequent study with an extended observation period (3–5 years) will provide more profound insights into the sustainability effects of e-learning and the evolution of these advantages when students enter the workforce.

Our longitudinal approach advances previous cross-sectional studies by demonstrating the evolution and sustainability of e-learning benefits over time. Unlike Wagino *et al.* [10] who focused on immediate outcomes, our 12-month observation period reveals that e-learning benefits actually intensify through continuous engagement, particularly in developing critical thinking capabilities and digital behavioral adaptations.

Future studies must investigate the moderating impact of contextual variables, including institutional features, the quality of technology infrastructure, and discrepancies in e-learning implementation. A multi-level analysis that accounts for nested structural data (students within programs, programs within institutions) will provide a more nuanced comprehension of the elements influencing the efficacy of e-learning across different analytical levels [64].

Building on our findings, several critical research directions emerge for advancing e-learning in vocational education. The strong relationship between E-Learning Usage Patterns and Digital Behavior Transformation (β = 0.682) indicates readiness for AI-powered personalization, warranting investigation into adaptive content delivery systems that adjust difficulty based on real-time critical thinking assessment, predictive analytics for early intervention, and natural language processing applications for automated feedback. Virtual and Augmented Reality technologies offer unprecedented opportunities through virtual laboratories for automotive diagnostics without equipment constraints, AR overlays that bridge digital learning with physical practice, and mixed reality collaboration spaces addressing the high importance of Social Support (β = 0.825). Multi-disciplinary replication studies across healthcare, business, computer science, and liberal arts programs would establish boundary conditions and test the model's transferability across diverse educational contexts with varying practical components and learning cultures.

Methodological innovations should move beyond self-report measures through technological advances including biometric monitoring (eye-tracking, EEG, galvanic skin response) to assess cognitive load and engagement intensity, learning analytics mining to reveal actual versus reported usage patterns, and longitudinal career tracking following graduates for 5+ years to correlate e-learning engagement with workplace performance. These research directions would advance theoretical understanding while providing actionable guidance for institutions investing in educational technology, ensuring vocational education remains relevant and effective amid rapid technological evolution and changing workplace requirements. The integration of emerging technologies, cross-cultural validation, and real-time adaptive systems represents the frontier of e-learning research, promising to transform how vocational skills are developed and sustained in the digital age.

9) Practical implications for education stakeholders

This study offers a practical framework for many stakeholders in vocational education. Institutional administrators prioritise investment in the establishment of a comprehensive social support system and systematic digital literacy initiatives. Resource allocation for faculty development and technological capacity enhancement must be equitably matched with investments in establishing learning communities and mentorship mechanisms that facilitate social interaction in a digital context.

These results underscore the significance of instructors and academic staff as digital learning facilitators who provide material and foster an atmosphere conducive to student engagement and cooperation. The development of competencies in building interactive digital learning activities and implementing effective incentive techniques is essential.

This research suggests that students must develop self-regulation skills and actively engage with digital learning platforms to achieve success in e-learning. Students must recognise that the advantages of e-learning are not acquired passively; they need active engagement in learning exchanges and the effective use of available resources.

These findings provide empirical support for policymakers and regulators in education to implement policies that promote the digitalization of vocational education, emphasizing the need for a comprehensive approach that addresses the technical, pedagogical, and social dimensions of digital transformation. The formulation of standards and frameworks for successful e-learning deployment must incorporate the insights gained from this research, acknowledging the intricate aspects that influence e-learning success [65].

The research findings emphasize the critical need for institutional leaders to adopt a systems-thinking approach when implementing e-learning initiatives. Rather than treating technology adoption as an isolated intervention, administrators must recognize that successful e-learning integration requires coordinated efforts across multiple organizational levels. This includes establishing cross-functional teams that include IT specialists, pedagogical experts, student support services, and academic leadership to ensure alignment between technological capabilities and educational objectives. Furthermore, the dominant influence of Social Support (β = 0.825) suggests that institutions should invest in comprehensive change management programs that address not only technical training but also cultural transformation toward collaborative digital learning environments. This holistic approach requires dedicated resources for ongoing professional development, peer mentoring networks, and systematic feedback mechanisms that allow for continuous improvement of digital learning ecosystems.

The longitudinal nature of this study reveals important implications for long-term strategic planning in vocational education institutions. The sustained impact of e-learning on Digital Behavior Transformation (β = 0.682) indicates that institutions should view digital learning investments as foundational infrastructure rather than temporary solutions. This perspective necessitates the development of multi-year implementation roadmaps that account for the gradual nature of behavioral change and skill development. Educational stakeholders must also consider the importance of creating flexible learning pathways that can adapt to evolving industry demands and technological advancements. The research suggests establishing partnerships with industry leaders to ensure that digital learning experiences remain relevant to professional practice while simultaneously developing internal capacity for rapid curriculum updates and technology integration. This forward-thinking approach positions institutions to leverage the cumulative benefits of sustained e-learning engagement while maintaining responsiveness to changing educational and professional landscapes.

10) Contribution to evidence-based digital learning practices

This study advances evidence-based digital learning techniques by offering empirically proven theoretical models to comprehend and anticipate the effects of e-learning deployment. The established model serves as a framework for assessing and continually enhancing e-learning systems by providing essential indicators that must be evaluated to ensure efficient deployment.

Identifying critical characteristics that influence the efficacy of e-learning offers pragmatic direction for diagnostic evaluation and intervention formulation. Institutions may use this approach to identify areas for improvement and formulate tailored intervention methods to maximise digital learning results. This methodical strategy may minimize trial-and-error in e-learning implementation and enhance the return on investment in educational digitalization.

The results about the impacts of mediation and causal processes within the model provide crucial insights into the sequencing and timing of implementing different components of the e-learning system. Recognizing that Digital Learning Interaction serves as a crucial mediator should guide implementation methods that emphasise social interaction ability rather than focusing on intricate learning outcomes [66].

The research demonstrates that investment in e-learning within vocational education can offer enduring and multifaceted benefits. Successful implementation requires a comprehensive strategy that accounts for the intricate interplay of technological, pedagogical, social, and motivational aspects influencing the efficacy of digital learning. The established model offers a comprehensive framework to facilitate the execution of evidence-based and sustainable e-learning in vocational education.

This research significantly advances the theoretical understanding of digital learning by demonstrating the complex interplay between cognitive, behavioral, and social factors in e-learning environments. The identification of Digital Learning Interaction as a crucial mediator ($\beta = 0.195$, $p < 0.001$) between e-learning usage patterns and the development of critical thinking provides empirical support for socio-constructivist learning theories in digital contexts. This finding challenges the traditional view of e-learning as primarily an individual, technology-mediated experience and instead positions it as a fundamentally social and collaborative process. The evidence-based framework developed in this study offers researchers and practitioners a robust theoretical foundation for designing e-learning interventions that prioritize interactive and collaborative elements. Moreover, the model's strong predictive power (R-square > 0.68) provides confidence in its utility for both explanatory and predictive purposes, enabling educational researchers to build upon these findings in diverse educational contexts and contribute to the development of more sophisticated theories of digital learning effectiveness.

The longitudinal methodology employed in this research establishes a new standard for evaluating the sustained impact of educational technology interventions. Unlike previous studies that focus on immediate outcomes, this research demonstrates the importance of measuring both short-term and long-term effects of e-learning implementation. The evidence of sustained benefits through Digital Behavior Transformation and Critical Thinking Development provides crucial validation for the investment in digital learning infrastructure. It supports the argument for longitudinal evaluation frameworks in educational technology research. The consistent predictive superiority demonstrated through Cross-Validated Predictive Ability Test (CVPAT) results (average loss difference = −0.381, $p < 0.001$) establishes benchmarks for model validation in educational research and provides methodological guidance for future studies. This contributes to the broader evidence base by demonstrating that well-designed e-learning interventions can produce measurable, lasting changes in student capabilities, thereby supporting policy decisions and institutional investments in digital learning technologies. The research also establishes important precedents for multi-dimensional outcome measurement that consider both cognitive development and behavioral transformation as essential components of educational effectiveness.

While our findings provide robust evidence for e-learning effectiveness in automotive engineering, their generalizability requires careful consideration across multiple dimensions:

Disciplinary Specificity. Automotive engineering's unique blend of theoretical knowledge and hands-on practice may limit direct transferability to other fields. Pure theoretical disciplines (philosophy, mathematics) or creative fields (art, music) may show different e-learning effectiveness patterns due to their distinct pedagogical requirements. The strong emphasis on practical skills in our context means findings may best generalize to similar technical fields like mechanical or electrical engineering.

Geographic and Cultural Context. Our study was conducted in Indonesian vocational institutions operating under the Merdeka Belajar curriculum framework. This context features specific characteristics: collectivist learning culture emphasizing peer collaboration, government-mandated digital literacy programs, and emerging digital infrastructure. Western educational systems with individualistic learning traditions or countries with mature digital ecosystems may yield different results. The high importance of Social Support ($\beta = 0.825$) in our model may partially reflect Indonesia's collectivist culture.

Institutional Variations. Our findings emerge from well-resourced vocational institutions with established industry partnerships. Institutions with limited resources, weak industry connections, or different pedagogical approaches may experience varied outcomes. The model's effectiveness likely depends on baseline institutional capacity for digital transformation.

Temporal Considerations. Educational technology evolves rapidly. Our data (2019–2023) captures a specific technological moment. Emerging technologies like AI tutors, VR laboratories, or quantum computing may fundamentally alter the relationships we observed. Future researchers should consider these temporal boundaries when applying our framework.

Demographic Factors. Our sample comprised traditional-age vocational students (18–22 years). Adult learners, part-time students, or those with extensive work experience may demonstrate different e-learning engagement patterns and outcomes.

Despite these boundaries, our model's core insight—that successful e-learning requires integrating technological, social, and cognitive dimensions—likely applies across contexts, though specific relationships may vary in strength and configuration.

V. Conclusion

This longitudinal research successfully revealed the sustainable impact of e-learning integration on automotive engineering students through SEM-PLS analysis of 225 respondents. The study's key contribution lies in demonstrating that e-learning benefits extend beyond immediate academic gains to fundamental transformations in digital behavior and critical thinking capabilities.

Social Support emerged as the dominant factor ($\beta = 0.825$, $p < 0.001$), confirming that effective e-learning requires robust social frameworks beyond technical infrastructure. E-Learning Usage Patterns substantially transformed Digital Behavior ($\beta = 0.682$, $p < 0.001$), preparing students for Industry 4.0 demands. The model's strong predictive capability ($R^2 > 0.68$) and CVPAT superiority validate its practical utility for evidence-based e-learning implementation.

Future research should extend observation periods to 3–5 years, conduct multi-disciplinary comparisons, integrate objective performance metrics, and explore emerging technologies like AI and VR in vocational contexts. These findings provide a comprehensive framework for sustainable e-learning implementation in vocational education.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Wagino Wagino: Conceptualization, methodology design, longitudinal study development, data collection oversight, statistical analysis using SmartPLS 4, writing—original draft preparation, supervision; Volodymyr Tymofiiv: Editing/reviewing, supervision, international perspective contribution, theoretical framework validation; Ken Polin: Editing/reviewing, supervision, engineering education expertise, critical review of methodology and findings; Milana Milana: Survey instrument development, data collection coordination, measurement model validation, writing—review & editing; Murni Astuti: Theoretical framework construction in educational psychology, literature review contribution, pedagogical insights on digital learning; Rahmat Desman Koto: Data acquisition, structural equation modeling analysis, results interpretation, manuscript drafting, data curation, visualization. All authors participated in the review and editing process, contributed to the interpretation of findings, and approved the final version of the manuscript.

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