Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 2, 1090-1102
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i2.4659

Modeling the influence of digital technical competence in animation creation on employability of vocational high school animation students using PLS-SEM

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Abstract: This study investigates the impact of digital technical competence in animation creation on the employability of vocational high school animation students using Partial Least Squares Structural Equation Modeling (PLS-SEM). The research highlights the importance of 21st-century skills, such as creativity, critical thinking, and collaboration, and their relevance to employability in digital industries. A survey conducted among 54 vocational students in Surabaya revealed that technical competencies, particularly in animation, significantly affect employability. The study's model demonstrates strong validity and reliability, confirming that the development of digital technical skills in animation is crucial for improving students' readiness for the job market. Findings emphasize the necessity of integrating these competencies into education systems to prepare students for evolving industry demands.
Keywords: *Animation creation, Digital technical competence, Employability, Vocational education, and PLS-SEM.*

1. Introduction

The importance of 21st-century skills in education is underscored by their influence on ensuring students possess the ability to learn and innovate, actively engage as information technology users, work effectively, and persevere using life skills [1]. The integration of 4.0 technology in learning signifies the professionalism of contemporary educators [2]. According to Öztürk [3], 21st-century skills express individual characteristics essential for becoming good citizens in terms of employment. These skills encompass cognitive, behavioral, and emotional development for both school and non-school aspects.

Aligned with this perspective, St. Louis, et al. [4] emphasize the prioritization of 21st-century skills, including creativity, innovation, critical thinking, problem-solving, decision-making, learning, and collaboration, crucial for connecting information technology in preparing children for future employment. The implementation of these skills is vital in school-based learning, representing the evolution from primitive to agrarian, industrial, and towards an informative society marked by digitalization Rahayu, et al. [5].

In the realm of digital competency, animation skills are paramount for preparing graduates to meet industry needs Anshori and Rohmantoro [6]. The mastery of digital animation competence, covering content creation and technical operational aspects, is crucial for effective educational outcomes [7]. The application of digital technology in learning, particularly through animation products, aligns with technological advancements, enhancing communication, initiating learning, delivering content, and evaluating digital-based learning [8].

History: Received: 10 December 2024; Revised: 22 January 2025; Accepted: 27 January 2025; Published: 8 February 2025
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To enhance human resources quality in Indonesia, technical competence in digital animation production is a primary focus, with its success indicated by increased employability in the job market [9]. Employability choices are influenced by teaching quality, social capital, and psychological capital [10]. The Teaching Factory model integrates school learning into real-world practice, allowing the construction of industrial knowledge [11].

In the current digital era, animation is a burgeoning field with increasing popularity. Competence in animation skills adds value to individuals, enhancing their employability in the job market [12]. The digital creation of animation aligns with industry needs, making the production process more effective, efficient, and industry-standard. Through technical animation skills, students can produce high-quality animations, leading to entrepreneurship opportunities. Critical thinking, creativity, communication, and collaboration are essential alongside technical skills for achieving expected job performance [13]. Teamwork is crucial in animation production, requiring specific skills in various areas.

Partial Least Squares Structural Equation Modeling (PLS-SEM) is employed to evaluate the influence of technical animation skills on employability. PLS-SEM is a statistical method used to analyse relationships in complex models, focusing on understanding cause-and-effect relationships among different variables within a theoretical framework [14]. This method is suitable for small research samples or when there is ongoing theoretical development, allowing for both predictive and explanatory approaches.

Those researches emphasize the significance of digital animation competence in employability, highlighting the evolving nature of these skills in response to technological advancements. The findings indicate a significant relationship between animation skills and employability, emphasizing the need for continuous development to meet the demands of the job market, with distinctions noted based on education and gender backgrounds. The application of PLS-SEM provides a robust analytical framework to understand the direct and indirect effects of these variables. Overall, the study underscores the importance of integrating 21st-century skills and digital competencies in education to prepare students for the challenges of the future job market.

2. Methodology

This study aims to investigate and explain the factors that influence the Digital Technical Competence of Animation Creation on student employability. The participants involved in this study were 12th-grade students at a public vocational high school in Surabaya. The selection process of the research participants was carried out by considering specific criteria in accordance with the study objectives. The students included in the participants of this study are 54 students who are in the animation department. The research model used in this research can be seen in Figure 1.

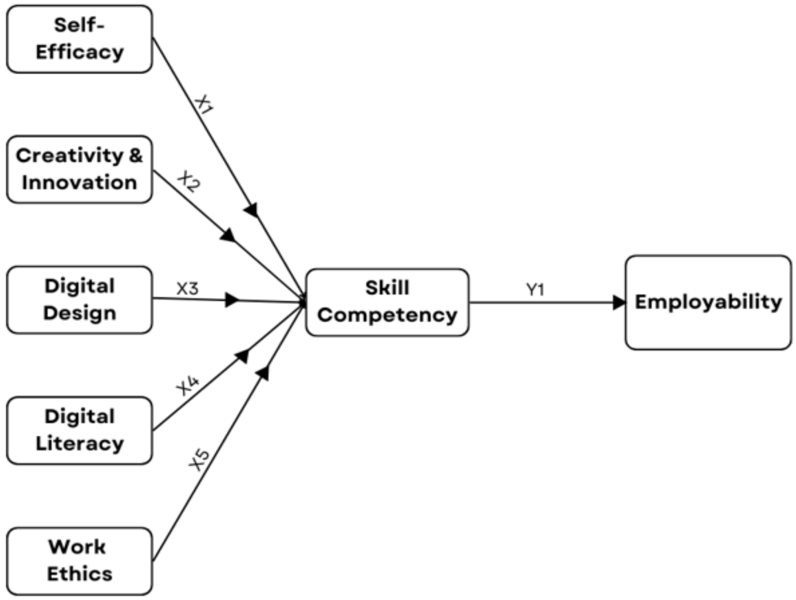

Figure 1.
Research model.

The instrument used in this research is a questionnaire. The questionnaire aims to determine the effect of digital technical competence in animation creation on employability. The indicators used in the questionnaire can be seen in Table 1.

Table 1.
Latent variables & item.

Latent Variable	Item
Self-efficacy (SE)	SE.1
	SE.2
	SE.3
Creativity & Innovation (CI)	CI.1
	CI.2
	CI.3
	CI.4
Digital Design (DD)	DD.1
	DD.2
	DD.3
Digital Literacy (DL)	DL.1
	DL.2
	DL.3
Work Ethic (WE)	WE.1
	WE.2
	WE.3
	WE.4
Skill Competency (SE)	SE.1
	SE.2
	SE.3
Employability (E)	E.1
	E.2
	E.3

The data collection for this research was conducted through a comprehensive survey that delved into the factors influencing the competence and employability levels of students.

Data collection for this research was carried out through surveys, due to its capabilities collects research data from actual observations, making it particularly suitable for investigation [15]. The survey in question is who are able to investigate the factors that influence students' level of competency and employability. The survey specifically focused on key elements such as self-efficacy, creativity and innovation, digital design, digital literacy, and work ethic. The survey used in data collection was a questionnaire for students. Data collection through surveys for questionnaires is carried out directly and closed with a time limit of 25 minutes for students to complete.

The questionnaire was distributed to students using a Likert scale, ranging from 1 to 5 was employed for measuring all indicators, with 1 indicating strong disagreement and 5 signifying strong agreement. The data collected was organized and summarized in, providing an overview of the variables under investigation and their relevance to the constructs being studied. This study employs PLS-SEM analysis using Smart-PLS Software, beginning with the formulation of a conceptual model based on theory. Subsequently, an evaluation of the outer model is conducted, involving the testing of construct validity and reliability, as well as the selection of variables that best represent the measured constructs.

In our study, researchers assessed the external validity of the model comprehensively, including discriminant and convergent validity. Emphasizing the pivotal role of discriminant validity in ensuring robustness in PLS-SEM models, we conducted a thorough examination of loading factors. In the context of reflective models, particular attention was given to outer model loadings, revealing the absolute contribution of each indicator in defining its latent variable. Standardized weights, known as measurement loadings, established connections between factors and indicators. With data automatically standardized in Smart PLS, loadings ranging from 0 to 1 were scrutinized for significance, where larger values indicate a more reliable measurement model, similar to item reliability coefficients in reflective models. In well-fitted reflective models, path loadings were expected to surpass the 0.60 threshold [16].

Simultaneously, convergent validity is assessed by evaluating the extent to which measured indicators contribute to the measurement of a specific construct. Utilizing the Average Variance Extracted (AVE) as a comprehensive test addresses convergent validity within reflective models. This metric encapsulates the average communality of each latent factor, offering insights into the convergence of indicators around their respective constructs. In a well-constructed model, it is imperative that the AVE exceeds the critical threshold of 0.5, a criterion established in prior research. Additionally, the AVE should surpass cross-loadings, indicating that latent factors should explain a minimum of half the variance exhibited by their associated indicators. AVE values below 0.50 suggest an imbalance, with error variance outweighing the variance explained by the factors [16].

Examining the AVE value is broken down through an Equation 1, where λ_i represents the component loading to the indicator and εi= 〚1-λ〛 _i,

$$AVE = \frac{\sum_{i=1}^{n} \lambda_i^2}{\sum_{i=1}^{n} \lambda_i^2 + \sum_{i=1}^{n} \varepsilon_i} \qquad (1)$$

Reliability testing is performed to measure the consistency, accuracy, and precision of an indicator in measurement. In SEM-PLS, reliability is assessed using the Composite Reliability (CR) parameter, calculated using the following Equation 2. An indicator is considered reliable if the CR value is > 0.7.

$$CR = \frac{\left(\sum_{i=1}^{n} \lambda_i\right)^2}{\left(\sum_{i=1}^{n} \lambda_i\right)^2 + \sum_{i=1}^{n} var(\varepsilon_i)} \qquad (2)$$

CR reflects the extent to which a group of indicators together provide consistent information about a latent variable.

3. Results

Employing SEM-PLS, our analysis delves into the intricate relationships within our research model, encompassing both the measurement (outer model) and structural (inner model) components of latent variables. The meticulous evaluation of the outer model assesses the validity and reliability of our measurement indicators, ensuring their effectiveness in capturing the nuances of latent constructs. Subsequently, the inner model evaluation scrutinizes the structural relationships, shedding light on the complex interdependencies among the latent variables.

By presenting and discussing the outcomes of both outer and inner model assessments, our study aims to provide a comprehensive understanding of the empirical patterns and associations governing the variables under investigation. The application of SEM-PLS enhances the interpretative depth of our research, offering valuable insights into the underlying mechanisms that shape our conceptual framework.

3.1. Evaluation of Measurement Models (Outer Model)

Embarking on the meticulous scrutiny of our measurement models, this section represents a pivotal juncture in our analysis, which includes Convergent Validity (CV) and Discriminant Validity (DV). Herein, we delve into the fundamental domains of validity, reliability, and hypothesis testing. The examination commences with a meticulous assessment of validity, dissecting loading factors and AVE to ascertain the efficacy of our measurement indicators in encapsulating the variance of latent constructs. Following this, the spotlight turns towards the reliability test, unveiling insights into the consistency and precision of our chosen indicators. The crescendo of this assessment culminates in hypothesis testing, encompassing both direct and indirect effects, unfurling the intricate tapestry of relationships within our research framework.

3.2. Validity Testing

The validity of the measurement model is then evaluated based on convergent and discriminant factors. Convergent Validity (CV) assesses the similarity of items with similar underlying principles. CV is evaluated using AVE and outer loading values, as recommended by Dang, et al. [17]. Table 2 displays AVE values above 0.50 for all constructs, and almost all outer loadings exceed 0.70, confirming the validity of the model. Loading factors of each indicator are visualized in Figure 2.

ISSN: 2576-8484
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DOI: 10.55214/25768484.v9i2.4659

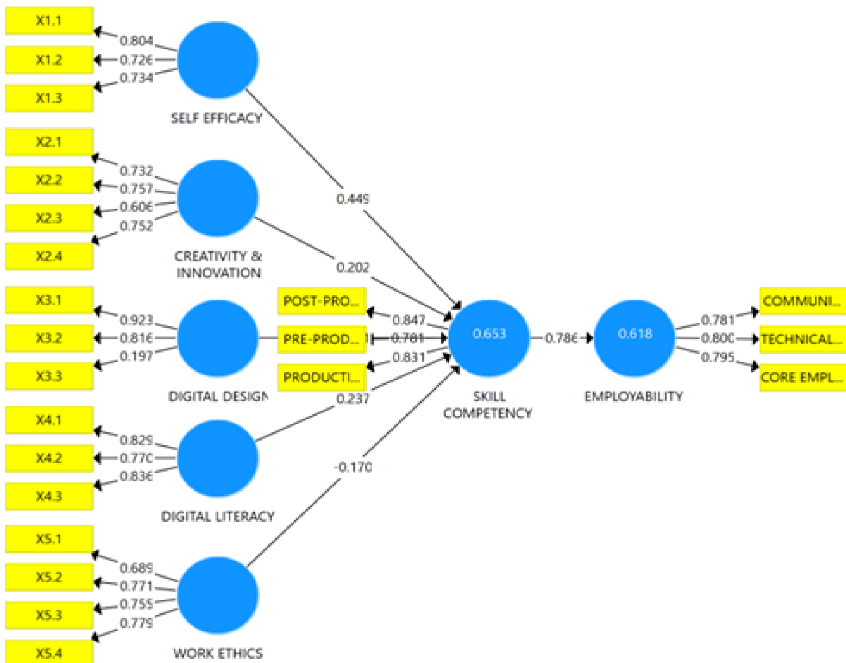

Figure 2.
Path diagram with convergent validity on each indicator.

Table 2.
Loading factors and AVE.

Latent Variable	Item	Outer loading	AVE
Self-efficacy (SE)	SE.1	0.804	0.510
	SE.2	0.726	
	SE.3	0.734	
Creativity & Innovation (CI)	CI.1	0.732	0.519
	CI.2	0.757	
	CI.3	0.606	
	CI.4	0.752	
Digital Design (DD)	DD.1	0.923	0.660
	DD.2	0.816	
	DD.3	0.798	
Digital Literacy (DL)	DL.1	0.829	0.627
	DL.2	0.770	
	DL.3	0.836	
Work Ethic (WE)	WE.1	0.689	0.571
	WE.2	0.771	
	WE.3	0.755	
	WE.4	0.779	
Skill Competency (SC)	SC.1	0.781	0.673
	SC.2	0.831	
	SC.3	0.847	
Employability (E)	E.1	0.781	0.562
	E.2	0.800	
	E.3	0.795	

Based on Figure and Table 2, It can be seen that the 21 indicators used to explain latent variables are valid because they meet the criteria, with a loading factor value exceeding 0.7 [18, 19]. Meanwhile, there are 2 invalid indicators, namely WE.1 and CI.3. This disclosure explains the strong validity of each of the indicators, highlighting their distinct relationships with their respective latent variables. The clarity seen in these associations emphasizes the precision and validity of the selected indicators in accurately representing and distinguishing the latent constructs under consideration. In essence, these findings underscore the careful selection and effectiveness of the indicators in capturing the various relationships in the conceptual framework of this study.

After further study, focusing on the convergence aspect, it should be noted that the AVE of each indicator in contributing to the specified construct exceeds the minimum threshold of > 0.5 [20]. This indicates a comprehensive and substantial contribution from each indicator to the overall construct or latent variable it represents. In essence, the indicators selected for this study show a satisfactory level of convergence, indicating that they collectively and meaningfully contribute to the formation and understanding of the broader construct, thus strengthening the robustness of the conceptual framework used in the study.

3.3. Reliability Testing

Reliability testing assesses in measuring the same latent variable in the outer model, with metrics like Cronbach's Alpha (α) and CR commonly used. Cronbach's α, ranging from 0 to 1, measures internal reliability, and Cronbach's α value above 0.6 is considered good [21]. CR gauges the consistency of indicators collectively in providing information about the latent variable, with a CR value above 0.7 indicating adequate reliability [22]. Cronbach's α and CR values for each latent variable are presented in Table 3.

In the reliability evaluation, which is an integral aspect of the research model, all latent variables showed Crobanch's α values exceeding the threshold of 0.6. While the overall the CR is said to be a better tool for measuring accurate reliability findings [23, 24]. CR value shows a value ranging from 0.70 and 0.90 which has a satisfactory to good interpretation [24]. In the Dijkstra-Henseler (ρA) value there are 5 variables that meet the threshold value consisting of CI, DL, WE, SC, and E. Meanwhile there are also variables whose Dijkstra-Henseler value is less than the threshold value, namely, DD and SE.

Table 3.
Factors' reliability.

Variable	Cronbach's α	ρ_A	CR
SE	0.684	0.646	0.834
CI	0.629	0.704	0.805
DD	0.742	0.646	0.722
DL	0.703	0.747	0.853
WE	0.631	0.740	0.836
SC	0.756	0.760	0.860
E	0.740	0.703	0.834

This compelling result attests to the commendable consistency, accuracy, and precision exhibited by each individual indicator in furnishing the essential information required to underpin its respective latent variable. The reliability measures affirm the robust internal consistency of the chosen indicators, instilling confidence in their ability to consistently and accurately capture the nuances of the latent variables they represent. This reliability underlines the dependability of the measurement instruments employed, reinforcing the credibility of the research findings and the fidelity of the data collected in support of the overarching objectives of the study.

Discriminant Validity (DV) guarantees that items score high on desirable constructs and poorly on irrelevant constructs. According to Quan, et al. [25] Table 4. displays the cross-loadings, which generally show high values for related constructs and low values for unrelated constructs. This facilitates the calculation of DV based on the results of [17].

Table 4.
Cross loadings.

Items	CI	DD	DL	E	SE	SC	WE
CI 1	0.732	-0.052	0.021	0.262	0.255	0.283	-0.020
CI 2	0.757	-0.006	-0.084	0.261	0.184	0.259	-0.335
CI 3	0.606	0.023	-0.030	0.214	0.185	0.222	-0.276
CI 4	0.752	-0.008	-0.010	0.126	0.473	0.376	-0.065
DD 1	-0.034	0.923	0.108	0.454	0.267	0.424	-0.130
DD 2	0.031	0.816	0.108	0.309	0.149	0.304	-0.021
DD 3	0.100	0.197	-0.149	0.090	-0.178	-0.061	0.093
DL 1	-0.047	0.177	0.829	0.282	0.279	0.342	-0.094
DL 2	-0.026	0.107	0.770	0.180	0.144	0.301	-0.131
DL 3	-0.006	0.058	0.836	0.397	0.160	0.351	-0.228
SE 1	0.371	0.240	0.182	0.408	0.804	0.606	-0.114
SE 2	0.186	0.355	0.271	0.293	0.726	0.480	0.064
SE 3	0.381	-0.028	0.081	0.196	0.734	0.401	-0.036
WE 1	-0.163	-0.116	-0.223	-0.339	-0.056	-0.240	0.689
WE 2	-0.149	-0.149	-0.090	-0.282	0.074	-0.194	0.771
WE 3	-0.090	-0.074	-0.182	-0.293	-0.078	-0.227	0.755
WE 4	-0.238	0.001	-0.063	-0.346	-0.059	-0.253	0.779

Hair, et al. [24] recommend evaluating the discriminant validity of measurement models by using the Fornell-Larcker Cross-loading Indicator Criterion. Discriminant validity tests aim to ensure that constructs are reflective and that indicators are stronger in correlation with the concepts they represent. Empirical procedures are used to separate the concepts. Details of the relationship between the model and the constructs can be found in Table 5. The Fornell-Larcker criterion is used to compare the square root of a construct's AVE with its correlation coefficient. Discriminant validity is verified when the square root of the AVE of a construct exceeds its correlation. The square root of AVE is used to compare the correlation between latent constructs according to the Fornell-Larcker cross-loading criterion Tao, et al. [23]. As shown in Table 5, the results confirm the discriminant validity values for Creativity & Innovation (0.714), Digital Design (0.720), Digital Literacy (0.812), Employability (0.792), Self-efficacy (0.755), Skill Competency (0.820), Work Ethics (0.749).

Table 5.
Discriminant validity (Fornell-Lacker).

	CI	DD	DL	E	SE	SC	WE
Creativity & Innovation	0.714						
Digital Design	-0.017	0.720					
Digital Literacy	-0.032	0.140	0.812				
Employability	0.288	0.448	0.359	0.792			
Self-efficacy	0.413	0.270	0.241	0.413	0.755		
Skill Competency	0.412	0.440	0.409	0.786	0.671	0.820	
Work Ethics	-0.218	-0.107	-0.188	-0.425	-0.047	-0.308	0.749

3.4. Hypothesis Testing of Direct and Indirect Effects

Hypothesis testing with the Bootstrap Resampling method is a statistical technique commonly used in SEM-PLS analysis to evaluate the significance of model parameters. In this study, there are 12 hypotheses, comprising 6 direct effects and 5 indirect effects, tested with a significance level of 5% (0.05). The t-statistic and p-value for direct and indirect effects are examined, and if the p-value is below the significance level, the null hypothesis (H_0) is rejected.

The structural model path coefficients, t-statistics and p-values are listed in Table 6. All variables meet the threshold and are accepted. The results show a significant influence and favorable impact of Skill Competency (SC) on Employability (E) ($\beta = 0.786$, $p < 0.05$). Furthermore, Creativity & Innovation (CI) ($\beta = 0.204$, $p < 0.05$), Digital Design (DD) ($\beta = 0.270$, $p < 0.05$), Digital Literacy (DL) ($\beta = 0.239$, $p < 0.05$), Self-efficacy (SE) ($\beta = 0.448$, $p < 0.05$), and Work Ethics (WE) ($\beta = 0.170$, $p < 0.05$) have a strong positive influence on Skill Competency (SC).

Table 6.
Hypothesis testing (direct effects).

PLS path	Original sample (O)	Standard deviation (STDEV)	T-statistics	p value	Remark
CI → SC	0.204	0.103	1.975	0.049	Supported
DD → SC	0.270	0.085	3.158	0.002	Supported
DL → SC	0.239	0.082	2.912	0.004	Supported
SE → SC	0.448	0.090	4.958	0.000	Supported
SC → E	0.786	0.037	21.389	0.000	Supported
WE → SC	0.170	0.084	2.017	0.044	Supported

Afterwards, the results of hypothesis testing for indirect effects, using skill competency as an intervening variable, are presented in Table 7. The mediating effect of digital technical competency in animation making on employability was investigated between the relationships of self-efficacy approach, creativity & innovation, digital design, digital literacy, and work ethics. Skill competency (SC) significantly mediated the relationship between creativity & innovation (CI) and employability (E) (t=1.966; p=0.050), Digital Design (DD) and employability (E) (t=3.030; p=0. 003), Digital Literacy (DL) and Employability (E) (t=2.855; p=0.004), Self-efficacy (SE) and employability (E) (t=4.913; p=0.000), and Work Ethics (WE) and employability (E) (t=1.989; p=0.047).

Table 7.
Hypothesis testing (Indirect effects).

PLS path	Original Sampel (O)	Standard deviation (STDEV)	T-statistics	p Values	Remark
CI → SC → E	0.160	0.081	1.966	0.050	Supported
DD → SC → E	0.212	0.070	3.030	0.003	Supported
DL → SC → E	0.188	0.066	2.855	0.004	Supported
SE → SC→ E	0.352	0.072	4.913	0.000	Supported
WE → SC → E	-0.134	0.067	1.989	0.047	Supported

3.5. Structural Model Evaluation (Inner Model)

In structural model evaluation in SEM PLS, one of the metrics used is the coefficient of determination (R^2). R^2 measures how well the structural model explains the variation in the endogenous or dependent latent variable. Ranging from 0 to 1, higher R^2 values indicate a better model's ability to explain the variation in the endogenous variable. The results of the coefficient of determination are presented in Table 8.

Table 8.
Structural model evaluation.

PLS Path	R square	R square adjusted
E	0.618	0.610
SC	0.653	0.617

4. Discussion

4.1. Evaluation on Hypothesis Testing

4.1.1. Hypothesis Testing of Direct Effects

Based on the hypothesis testing results using the Resampling Bootstrap method, it can be revealed that there is a positive direct effect from the independent latent variables of self-efficacy, creativity and innovation, digital design, digital literacy, and work ethic on skill competency as the dependent latent variable. Furthermore, skill competency also exerts a significant effect on Employability, as evidenced by p-values less than the 0.05 significance level.

The test results elucidate that each facet of skill and competency, starting from self-efficacy, creativity and innovation, digital design, digital literacy, to work ethic, constitutes crucial elements in fulfilling the skill competency of every learner to thrive and innovate in the 21st-century life [26] particularly in the digital era, especially for those focusing on digital animation careers [27]. Furthermore, the fulfilment of all the components of skill competency, starting from pre-production, production, to post-production, significantly impacts an individual's employability in the digital industry. All these factors serve as assurances for learners to not only survive but also innovate in the real world.

In essence, the findings underscore the importance of a holistic approach to skill development encompassing various facets, providing a comprehensive foundation for learners, especially those aspiring to excel in digital animation, to navigate the challenges and opportunities presented by the dynamic landscape of the 21st century. The implications extend beyond academic settings, emphasizing the practical significance of cultivating a diverse skill set for future success and adaptability in the digital realm [28].

4.1.2. Hypothesis Testing of Indirect Effects

Based Through rigorous hypothesis testing on indirect effects, it is evident that each independent latent variable, ranging from self-efficacy, creativity and innovation, digital design, digital literacy, to work ethic, significantly exerts an indirect influence on the dependent latent variable employability through independent latent variable of skill competency. The substantiated significance, reflected in p-values below the 0.05 threshold, reinforces the intricate relationship between the elements that shape individual skill competency and their subsequent impact on employability.

These findings underscore a more nuanced understanding: a comprehensive mastery of individual skill competency elements translates directly to enhanced employability. The study makes a compelling case that employability experiences a noteworthy boost when individuals actively cultivate and refine competencies tailored to contemporary life demands. The implication is clear – professionals thrive not only by meeting the immediate requisites of the digital era but by strategically developing competencies that contribute meaningfully to societal advancement.

In essence, this research goes beyond a mere exploration of the correlation between skill competency and employability; it serves as a clarion call for a proactive, strategic approach to skill development. The results advocate for a paradigm shift in education, urging institutions and policymakers to adopt holistic and adaptive strategies that align seamlessly with the ever-evolving demands of the contemporary workforce [29].

4.2. Evaluation on Structural Model (Inner Model)

The findings derived from the regression analyses of endogenous or dependent latent variables – Employability and Skill Competency, reveal noteworthy insights. The R Square values serve as key indicators, elucidating the extent to which the selected independent variables contribute to the variance in each respective dependent variable. For Employability, the R Square of 0.618 suggests that 61.8% of the variability in employability can be attributed to the independent variables in the model. The adjusted R Square, accounting for potential impacts of additional independent variables, is 0.610, reflecting 61% explanatory power. In the case of Skill Competency, the R Square of 0.653 signifies that approximately 65.3% of the variance can be explained by the chosen independent variables. The adjusted R Square, considering the influence of potential additional variables, is 0.617 or 61.7%. These robust R Square values underscore the model's significant explanatory capacity, emphasizing the importance of the incorporated variables in comprehending and predicting variations in Employability and Skill Competency.

5. Conclusion and Recommendation

5.1. Results Conclusion

The study concludes that technical animation competence significantly impacts the employability of vocational high school students. Through PLS-SEM analysis, it was revealed that digital design, digital literacy, creativity, innovation, self-efficacy, and work ethic positively affect skill competency, which in turn, directly influences employability. This confirms the importance of these variables in preparing students for careers in the animation industry.

5.2. Research Implication

The findings underscore the need for educational institutions to integrate digital technical competence in their curricula, particularly in vocational education. By doing so, schools can better prepare students to meet the demands of the modern job market. The study's emphasis on practical skills such as creativity, critical thinking, and collaboration reinforces the value of developing holistic education programs that equip students with both technical and soft skills.

5.3. Research Limitation

This research is limited to a small sample size of 54 students from a single vocational school in Surabaya, Indonesia. The findings may not be fully generalizable across broader contexts, such as other regions or different levels of educational institutions. Moreover, the study primarily focuses on the technical aspects of animation, which may not encompass the full range of competencies required across other digital industries.

5.4. Recommendation for Future Research

Future studies should consider expanding the sample size to include students from various regions and institutions to gain a broader understanding of digital technical competence and employability. Additionally, research can explore the influence of other 21st-century skills, such as leadership and entrepreneurship, on employability in the digital industry. Lastly, longitudinal studies would be valuable in tracking how the development of technical competencies impacts employability over time.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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