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How Does the Future Economics Teacher Against Digital Economics? The Perspective of Economics Behaviour and Role of Social Support

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Abstract

The study aims to find a structural fit model related to students' readiness to face the digital economy in the perspective of irrational behavioral economic theory. The study uses quantitative Explanatory research with a population of undergraduate students of Economics Education at the East Java PGRI College and uses a proportional random sampling with total of 351 students. Data were collected by questionnaires using linkert scale and were analysed by SEM-PLS data analysis . The findings show that digital economic skills don't significantly mediate the relationship between herd behavior, loss aversion, and student readiness. However, the digital economy succeeded in mediating the influence of confirmation bias on student readiness because of helped reduce the impact of confirmation bias on student readiness by offering access to diverse information and developing critical thinking skills. This study contributes are become theoretical literature on the functional relationship between irrational behavior, digital economic skills, social support and student readiness studied in the context of behavioral economics. It can be a reference for developing educational models in digital era learning and reference for further researchers to develop appropriate policy recommendations by involving several related stakeholders.

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INTRODUCTION

In order to realize the Vision of Golden Indonesia 2045, the government has planned extraordinary steps so that economic growth in Indonesia continues to increase, namely by developing the digital economy (Hartarto, 2023). In the world of education, there is a concept of Disruptive Education which can improve the competence of human resources in facing the digital economy which will certainly shift the previous competences possessed by prospective educators, especially in higher education (Gejendhiran et al., 2020). There are at least 5 competencies in disruptive education; educational competence, competence for technological commercialization, competence of globalization, competence in the future strategies, and counselor competence (Gejendhiran et al., 2020). The full involvement of students in preparing themselves to achieve disruptive education competencies is very important in determining their success. This is in line with the theory of involvement which explains that good outcomes are less focused on the efforts made by educators, but more on the efforts made by students in learning (Faisol & Astuti, 2024). In the theory of involvement, input and environment are important things to determine an outcome. However, in achieving outcomes, not all students behave rationally. In fact, many students behave irrationally in meeting their needs, especially in improving their personal competence (Kurniawan, 2020; Mi & Coffman, 2019). In line with this, there is a behavioral economic theory that can be used to study the irrational behavior of students, namely Richard Thaler's theory.

Richard Thaler's theory explains that there are several aspects that are the reasons why individuals are irrational, including fear of potential losses compared to the benefits obtained (Loss Aversion); overestimating goods that have been purchased or owned, so that their value is considered higher than the market price or objective value (Endowment Effect); being trapped in a favorite choice, so that you only want to confirm information that supports that choice and ignore other alternatives that are more rational and objective (Confirmation Bias); the tendency to follow so that decisions taken tend to follow what other people in their group do (Herd Behavior); and making conclusions based on invalid data, so that you are more confident in interesting and specific information, but in fact it cannot be generalized and does not apply in general (Survivor Behavior) (Bauer & Capron, 2020). Based on the five aspects of irrational behavior, in the context of this study, three aspects will be examined, including Loss Aversion, Herd Behavior, and Confirmation Bias. These three aspects tend to emerge when individuals consider their decisions in interacting and providing social impacts for others, which in this case are related to the decision to increase digital economic capabilities (Li, 2023; Molins et al., 2023; Wahyono et al., 2021;Barberis, 2018).

There have been many studies that explain the readiness of prospective educators as seen from various variables and research methods (Anggraeni et al., 2024; Erlinda Yustin et al., 2024; Faisol & Astuti, 2024; Roofiq et al., 2024). However, until now there has been no research that explains the readiness of prospective educators which includes considerations of digital skills and disruptive education. In addition, several facts also show that not all students behave rationally in improving their competence, but many students also behave irrationally in improving their personal competence (Kurniawan, 2020; Mi & Coffman, 2019). This fact can be studied in the perspective of Richard Thaler's behavioral economic theory which is reflected in three aspects, namely loss aversion, herd behavior, confirmation bias. There are several studies that examine irrational behavior (Irawan & Widjaja, 2021; Kurniawan, 2020; Vuorio et al., 2018; Wahyono et al., 2021). However, several studies conducted so far have only focused on individual behavior in general without involving the education sector as a fundamental aspect that will shape future generations, especially in the digital economy era. That is why this study is important to be conducted by looking at the existence of the education sector which also plays an important role in supporting Indonesia's economic growth through the formation of quality human resources. To deepen the study of student readiness through a behavioral economics perspective, this study also considers the aspect of social support. Individuals with good social support tend to have high well-being and high levels of self-confidence, which greatly influences individuals to consider their decisions. (Diener & Tay, 2015). There are several aspects shows the relationship between social support and self-readiness, including life satisfaction, positive influence, and negative influence (Siedlecki, 2015). For this reason, this study includes social support as a moderating variable that will strengthen or weaken the influence of students' irrational behavior on students' readiness to face the digital economy.

Based on the flow of thought that has been discussed, this research aims to construct structural model of student rediness by future economics teacher to be up against digital economics. Exploratory research on student readiness utilizing Richard Thaler's behavioral economic theory and disruptive education theory can be a significant solution approach in the digital economy era. This theoretical collaboration offers an in-depth perspective on individual motivation and incentives in decision making including students who prepare their competencies to face the digital economy. In the context of education, this understanding can be used to design learning programs that are more interesting and in accordance with student preferences. In addition, the results of this study will provide a foundation for understanding how students optimize their decisions in improving digital economic competencies, this will be able to help related parties to compile a curriculum that is more in accordance with student readiness. Thus, this study provides a valuable contribution in efforts to improve Human Resources in the digital economy in order to realize the Vision of Golden Indonesia 2045.

METHODS

This study uses a quantitative Explanatory research approach that aims to connect different patterns but have a relationship and produce a suitable structural model (fit). Therefore, a relationship can be formulated that can be seen in the research design in Figure 1.

The population of this study used students of the S1 Economic Education Study Program at PGRI Colleges in East Java, totaling 10 Colleges. These colleges were chosen because they have similar characters, are consistent in producing prospective educators and have collaborated to improve the quality of learning for their students with a total of 2,776 students. The sampling technique in this study used probability sampling with the

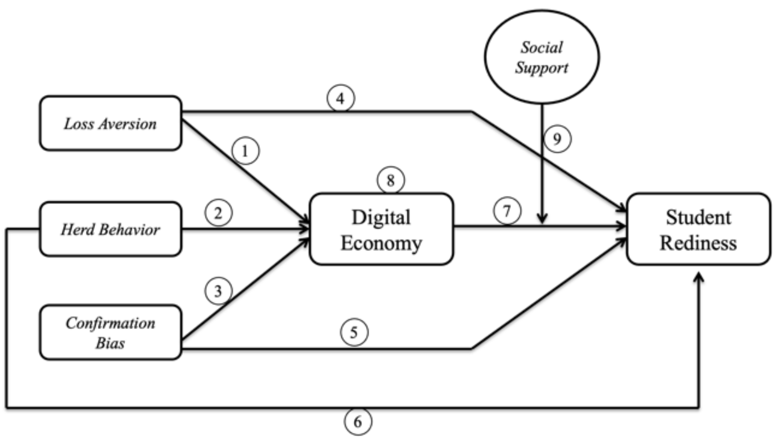

Figure 1. Relationship Patterns Between Variables

technique taken, namely proportional random sampling and produced a sample of 351 students. The data in this study were collected by distributing closed questionnaires to S1 Economic Education students at PT PGRI in East Java. The measurement scale uses a five-scale linkert scale which scale 5 means "strongly agree", scale 4 means "agree", scale 3 means "netral", scale 2 means "disagree" and scale means "strongly disagree".

Loss Aversion calculated by using four indicators are sensitive to risk of loss, optimism for future, trust in partners and careful viewing of opportunity. The indicators of herd behavior are tendency to imitate, the drive to be different, follow along tend, and encouragement to follow friends. Confirmation bias using indicators of individual information belief, though of inenviromental condition, and the trustworthiness of educational investment. As a mediation variable digital economics calculate by indicators cognitive skill, technology skill, management and engagement skill. Indicators of social support are life satisfaction, positive effect and negative effect. For the last variable is student rediness calculated by using indicators educational competence, competence for technological commercialization, competence of globalization, competence in the future strategies and conselor competence. The questionnaire has been validated by using 30 respondent of future economics teacher and the result shows that questionnaire has been valid and reliable.

This study will utilize Confirmatory Factor Analysis (CFA). The data analysis process is carried out through steps that follow the framework described by (Hair et al., 2019) which includes: 1) evaluation of the outer loading model, which involves construct validity & reliability and discriminant validity; 2) evaluation of the inner model through the use of the coefficient of determination (R2), effect size (F2), predictive relevance (Q2); and 3) testing the hypothesis or model fit through direct effect evaluation, indirect effect evaluation, and GoF (Goodness of Fit) criteria testing.

RESULT AND DISCUSSION

Evaluation of Measurement Model (Outer Model)

The evaluation of the outer model is carried out through the validity and reliability test of the research model using reflective indicators in testing its validity through convergent validity and discriminant validity of the indicators forming the latent construct. The reliability test of the research model is carried out by measuring the composite reliability and conbach's alpha values.

Convergent Validity

Convergent validity aims to determine the validity of each relationship between indicators and their latent variables. Convergent validity of the measurement model with reflective indicators is assessed based on the

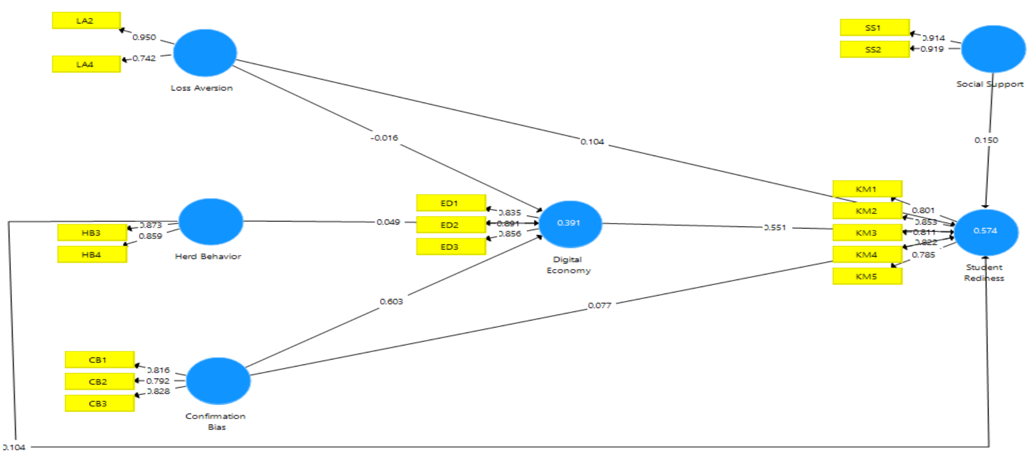

Figure 2. Structural Fit Model

correlation between item scores or component scores with latent variable scores or construct scores calculated using PLS. Loading factor values above 0.7 are said to be ideal and valid (Hair JR et al., 2020). However, loading factor values above 0.5 are also acceptable as long as the value is not below 0.5. Based on the test results, it was found that each loading factor value representing each indicator has a value of >0.7, which means that the value is said to be ideal or valid.

In addition, in assessing convergent validity, one of the measures often used is the Average Variance Extracted (AVE), which measures the proportion of variance explained by the construct compared to the variance caused by measurement error. This AVE value is generally considered adequate if it exceeds 0.5, which means that more than half of the variance of the indicators is explained by the latent construct (Hair JR et al., 2020). Based on the results of the analysis in our study, it can be concluded that the AVE values for several main constructs studied indicate a satisfactory level of convergent validity with AVE values greater than 0.5. Specifically, the AVE values obtained can be seen in Table 1.

Discriminant Validity

In assessing discriminant validity, there are two criteria that are often used, namely the Fornell–Larcker criteria and the heterotrait–monotrait ratio (HTMT), as expressed by (Hair et al., 2019). The Fornell–Larcker criterion suggests that for each construct in the model, the square root of the Average

Table 1. Convergent Validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Confirmation Bias	0.743	0.747	0.853	0.660
Digital Economy	0.825	0.829	0.896	0.741
Herd Behavior	0.667	0.669	0.857	0.750
Loss Aversion	0.663	0.942	0.840	0.727
Moderating Effect 1	1.000	1.000	1.000	1.000
Social Support	0.810	0.810	0.913	0.840
Student Rediness	0.873	0.875	0.908	0.664

Source: Processed primary data (2024)

Table 2. Fornell-Larcker Criteria

	Confirmation Bias	Digital Economy	Herd Behavior	Loss Aversion	Moderating Effect 1	Social Support	Student Rediness
Confirmation Bias	0.812						
Digital Economy	0.624	0.861					
Herd Behavior	0.452	0.320	0.866				
Loss Aversion	0.050	0.016	0.038	0.853			
Moderating Effect 1	-0.014	-0.033	0.079	-0.063	1.000		
Social Support	0.646	0.555	0.372	0.076	0.025	0.917	
Student Rediness	0.569	0.717	0.375	0.132	-0.007	0.552	0.815

Source: Processed primary data (2024)

Variance Extracted (AVE) should be greater than the highest correlation that construct has with other constructs. This aims to ensure that each construct in the model is more able to explain the variance of its own indicators than it is related to other constructs. On the other hand, HTMT serves to estimate the correlation between different factors, in order to assess whether the constructs are truly different from each other.

In order for the difference between two factors to be considered adequate, the HTMT value obtained must be significantly lower than 1. As a general rule, HTMT values below 0.9 are considered adequate, while a more recommended threshold is below 0.85, to ensure stronger discriminant validity (Hair et al., 2019). Table 3 of our study presents the inferential statistics for HTMT values, where the values shown are below the threshold of 0.85, indicating good reliability in ascertaining the differences between the constructs studied. These results strengthen the conclusion that the constructs in our model have adequate discriminant validity, so that each construct can be considered as a unique entity and different from each other in the research model.

Reliability of Indicators

One alternative metric that is often used to assess the reliability of an indicator is to examine outer loadings, which is a measure of how much of the variance of the observed variables can be explained by the underlying latent construct, as explained by (Hair et al., 2019). These outer loadings provide an overview of the extent to which the indicators in the model are closely related to the intended latent construct, and serve to assess the strength of the relationship between the observed variables and the latent construct. As a general guideline, an adequate outer loading value must exceed a minimum threshold of 0.7 to ensure that each indicator has a strong enough contribution to explaining the variance of its latent construct (Hair JR et al., 2020). In our study, the outer loading results presented in Table 4 show that all tested construct indicators have adequate values, where each outer loading value successfully exceeds the minimum threshold of 0.7. This indicates that the indicators used in the model have good reliability and are able to explain most of the variance associated with their respective latent constructs. These results also confirm the strong measurement validity in the study, which supports the accuracy of the findings obtained.

Evaluating of Inner Model

Structural model assessment is used to evaluate the effects of linear regression between endogenous constructs by mapping the pattern of relationships between various constructs. This model helps assess the influence of one construct on another, identify the strength and direction of the relationship, and test hypotheses about variable interactions.

Table 3. The Heterotrait-Monotrait (HTMT)

	Confirmation Bias	Digital Economy	Herd Behavior	Loss Aversion	Moderating Effect 1	Social Support	Student Rediness
Confirmation Bias							
Digital Economy	0.792						
Herd Behavior	0.646	0.431					
Loss Aversion	0.119	0.048	0.065				
Moderating Effect 1	0.021	0.036	0.096	0.075			
Social Support	0.829	0.681	0.507	0.126	0.075		
Student Rediness	0.702	0.841	0.491	0.170	0.065	0.653	

Source: Processed primary data (2024)

Table 4. Outer Loading

	Confirmation Bias	Digital Economy	Herd Behavior	Loss Aversion	Moderating Effect 1	Social Support	Student Rediness
CB1	0.816						
CB2	0.792						
CB3	0.828						
Digital Economy *Social Support					1.301		
ED1		0.835					
ED2		0.891					
ED3		0.856					
HB3			0.873				
HB4			0.859				
KM1							0.801
KM2							0.853
KM3							0.811
KM4							0.822
KM5							0.785
LA2				0.950			
LA4				0.742			
SS1						0.914	
SS2						0.919	

Source: Processed primary data (2024)

Thus, the structural model provides deeper insight into the dynamics between variables and supports the validation of the theory through empirical data. Inner model can be evaluated by using collinearity assessment, and coefficient of determination as shown below:

Collinearity Assessment

To identify potential collinearity in a structural model, one of the commonly used metrics is tolerance or variance inflation factor (VIF), as recommended by (Hair JR et al., 2020) and (Legate, 2020) VIF is used to measure how much the variance of the regression estimate increases due to the correlation between independent variables in the model. As a general guideline, a VIF value below 5 indicates that there is no significant collinearity problem among the indicators, so that the variables in the model can be considered independent of each other. Based on the results of the analysis presented in Table 5, all indicators of the tested constructs have VIF values below the threshold of 5, which confirms that there is no significant collinearity among the indicators. This shows that the model built is free from the influence of collinearity, so that the results of the regression estimation can be considered accurate and valid for further interpretation. With the absence of significant collinearity, this model can be relied on to assess the relationship between variables more precisely and in depth.

Table 5. Collinearity Assessment

	VIF
CB1	1.464
CB2	1.479
CB3	1.487
Digital Economy * Social Support	1.000
ED1	1.726
ED2	2.118
ED3	1.893
HB3	1.335
HB4	1.335
KM1	1.860
KM2	2.301
KM3	2.011
KM4	2.091
KM5	1.804
LA2	1.327
LA4	1.327
SS1	1.860
SS2	1.860

Source: Processed primary data (2024)

Coefficient of Determination

The coefficient of determination, represented by the R^2 value, describes how much of the variance in the dependent variable can be explained by one or more predictor variables in a model. The R^2 value ranges from 0 to 1, where the closer it is to 1, the better the model's ability to predict the dependent variable. In general, this value is used to evaluate the predictive accuracy of a structural model. According to (Hair et al., 2019), there are several categories used to assess the explanatory power of R^2: a value of 0.19 is considered weak, 0.33 indicates moderate explanatory power, and 0.67 reflects strong power. The results of the data analysis in this study indicate that the model has good predictive ability in explaining the dynamics of variance in both constructs, as summarized in Table 6. Thus, this model provides strong insight into the influence of these variables in explaining variation in the dependent construct, as well as strengthening the theoretical validity of the hypothesized relationships.

Table 6. R^2 (Coefficient of Determination)

	R Square	R Square Adjusted
Digital Economy	0.391	0.386
Student Rediness	0.574	0.567

Source: Processed primary data (2024)

Standardized Root Mean Square Residual (SRMR)

Standardized root mean square residual (SRMR) is an absolute measure to assess the goodness-of-fit (GoF) in a model, which is calculated based on the difference between observed and predicted correlations. This measure is very suitable for use in PLS-SEM (Partial Least Squares Structural Equation Modeling) based models as suggested by (Sarstedt et al., 2021). According to (Hair et al., 2019), an SRMR value below 0.10, or more conservatively, below 0.08, indicates that the model has a good fit. In this study, the model we developed showed an SRMR value of 0.060. This value is below the threshold of 0.08, indicating that the model has a good fit. With a strong SRMR value, it can be concluded that our model as a whole is able to describe the relationship between observed and predicted variables quite accurately, and provides strong support for the validity of the structural model used in this study.

Hypothesis Testing

To test the hypotheses related to the direct and indirect relationships in the model, we used the bootstrapping procedure by (Hair et al., 2019), to assess the statistical significance of the resulting coefficients. The results of this analysis are presented in Table 7, which includes significant direct and indirect effects, as well as additional information such as means, standard deviations, t-values, and p-values. The table shows that the hypotheses regarding the direct effect have p-values that vary between 0.000 and 0.863. From these results, there are several hypotheses that do not meet the established significance criteria, namely p-values above 0.05. Furthermore, to assess the moderation effect, we refer to the methodology described by (Hair et al., 2019) and (Sarstedt et al., 2021). The results of the analysis show that the p-value for social support is greater than 0.05, indicating that social support does not function as a moderating variable.

In the mediation analysis, we applied the bootstrapping method to assess whether the Digital Economy has a significant mediation effect. The results of the analysis of table 8 show that the digital economy does not show a significant mediation effect on herd behavior and loss aversion, which means that the digital economy did not succeed in mediating the influence of herd behavior and loss aversion on student readiness. However, the digital economy succeeded in mediating the effect of confirmation bias on student readiness with a significant p-value (0.000 <0.05) as seen in Table 8.

Confirmation bias tends not to affect student readiness because this bias usually occurs in contexts where individuals have previous experience or have taken action. In this case, students may not have enough experience or information related to the new situation, so they are more open to accepting different perspectives and information. The Cognitive Dissonance Theory, explained by Leon Festinger, explains that individuals tend to seek information that supports their beliefs. However, in the context of student readiness, students who are in the early stages of learning are more likely to seek and accept new information, without getting stuck in existing beliefs (Gatlin et al., 2019). Previous research has also shown that confirmation bias is more influential in individuals who have formed strong views on a topic (Nazaretsky et al., 2021; Peters, 2022; Talluri et al., 2018). Therefore, in the context of education, students who are

Table 7. Conclusion of Direct Effect Hypothesis Testing

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Conclusion
Confirmation Bias -> Digital Economy	0.603	0.602	0.046	13.031	0.000	Supported
Confirmation Bias -> Student Rediness	0.077	0.073	0.060	1.282	0.200	Not Supported
Digital Economy -> Student Rediness	0.551	0.550	0.052	10.682	0.000	Supported
Herd Behavior -> Digital Economy	0.049	0.049	0.051	0.965	0.335	Not Supported
Herd Behavior -> Student Rediness	0.104	0.106	0.050	2.074	0.039	Supported
Loss Aversion -> Digital Economy	-0.016	-0.014	0.059	0.280	0.780	Not Supported
Loss Aversion -> Student Rediness	0.105	0.106	0.051	2.055	0.040	Supported
Moderating Effect 1 -> Student Rediness	0.006	0.007	0.032	0.173	0.863	Not Supported
Social Support -> Student Rediness	0.150	0.157	0.062	2.403	0.017	Supported

Source: Processed primary data (2024)

Table 8. Conclusion of Indirect Effect Hypothesis Testing

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Confirmation Bias -> Digital Economy					
Confirmation Bias -> Student Rediness	0.332	0.331	0.041	8.078	0.000
Digital Economy -> Student Rediness					
Herd Behavior -> Digital Economy					
Herd Behavior -> Student Rediness	0.027	0.027	0.028	0.968	0.333
Loss Aversion -> Digital Economy					
Loss Aversion -> Student Rediness	-0.009	-0.007	0.032	0.281	0.779

Source: Processed primary data (2024)

in the process of learning and developing new skills, in this case digital economic skills, are more likely to consider various information and perspectives, which reduces the influence of confirmation bias on their readiness to learn.

Herd behavior and loss aversion do not have a significant effect on the digital economy due to the unique characteristics of the digital environment. Herd behavior involves the tendency of individuals to follow the actions of others, but in the digital world, users have better access to objective data and analysis (Gächter et al., 2022). This allows them to make more rational decisions, in accordance with the Theory of Rationality, where individuals seek to maximize benefits based on available information, rather than simply following the group. On the other hand, loss aversion, explained in the Prospect Theory by Kahneman and Tversky, suggests that individuals are more averse to losses than to gains (Mrkva et al., 2020). However, in the context of the digital economy, access to information and online reviews increases users' confidence in taking risks, thereby reducing the negative impact of loss aversion. Social interactions on digital platforms also encourage the sharing of positive experiences, which helps reduce the fear of loss (Vedadi & Greer, 2021). Thus, a transparent and informative digital environment reduces the influence of herd behavior and loss aversion in economic decision making.

CONCLUSION

Based on the results of the testing and discussion of this study, it can be concluded that digital economic skills do not show a significant mediation effect on irrational herd behavior and loss aversion, which means that digital economic skills do not succeed in mediating the influence of irrational herd behavior and loss aversion on student readiness. However, the digital economy succeeds in mediating the influence of irrational confirmation bias behavior on student readiness with a significant p-value ($0.000 < 0.05$).

In order to improve the quality of this research, suggestions that can be given to further researchers related to research are based on the calculation of R2 with the presence of several other variables that can affect students' readiness in facing the digital economy, so it is hoped that further researchers can develop other variables outside the variables that have been studied in order to have more varied results. This research result practically can be used as determinant of curriculum development or digital competency training.

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