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The Effect Of Digital Competence, Performance Expectancy, And Facilitating Conditions On Digital Economic Empowerment: The Role Of Transformative Capacity As An Intervening Variable On Business Actors In Jakarta, Surabaya, Bandung, And Medan

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Abstract

The use of digital technology in economic activities has continued to increase, but its utilization does not necessarily generate economic benefits directly. This study aims to examine the effects of digital competence, performance expectations, and facilitating conditions on digital economic empowerment, with transformative capacity as an intervening variable. The study employed a quantitative approach using secondary data from the Digital Transformation Adoption, Social Resilience, and Community Empowerment Outcomes in Post-Pandemic Indonesia dataset, consisting of 544 observations. The data were analyzed using Partial Least Squares-Structural Equation Modeling (PLS-SEM) with SmartPLS. The results show that digital competence has a positive and significant effect on transformative capacity (β = 0.245; p = 0.001), whereas performance expectancy has no significant effect (β = 0.044; p = 0.530). Facilitating conditions have a positive and significant effect on transformative capacity (β = 0.165; p = 0.038), while transformative capacity has a positive and significant effect on digital economic empowerment (β = 0.424; p < 0.001). Regarding the direct effects on digital economic empowerment, performance expectancy has a significant effect (β = 0.154; p = 0.019), whereas digital competence (β = 0.042; p = 0.554) and facilitating conditions (β = 0.085; p = 0.251) do not have significant effects. The indirect effect analysis indicates that transformative capacity mediates the relationship between digital competence and digital economic empowerment (β = 0.104; p = 0.002) and between facilitating conditions and digital economic empowerment (β = 0.070; p = 0.046), but does not mediate the relationship between performance expectations and digital economic empowerment (β = 0.019; p = 0.531). These findings indicate that the economic benefits of digitalization are

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more evident when technology utilization is accompanied by the capacity to make changes in business or community activities.

Keywords: Digital Competence, Performance Expectancy, Facilitating Conditions, Transformative Capacity, Digital Economic Empowerment

INTRODUCTION

The development of digital technology has transformed the way businesses conduct economic activities, from marketing and transactions to operational management to expanding market reach. The use of social media, marketplaces, and digital financial services opens up opportunities for micro, small, and medium enterprises (MSMEs) to increase efficiency and strengthen competitiveness in an increasingly dynamic business environment. However, digital transformation is not simply understood as the process of adopting devices or applications, but also as an effort to integrate technology into business strategies and models to generate sustainable economic value. Prakasa and Jumani (2024), through a study of 330 small businesses in East Java, found that digital capabilities influence digital business transformation and business performance, while digital business transformation mediates the relationship between digital capabilities and performance. In line with these findings, Liu et al. (2024) showed that dynamic capabilities can drive business model innovation and the performance of small and medium enterprises, with digital transformation strengthening this relationship. These two studies emphasize that the success of digitalization is not only determined by the availability of technology, but also by the ability of business actors to utilize it to generate strategic changes and economic benefits (Liu et al., 2024; Prakasa & Jumani, 2024).

In the Indonesian context, the opportunities for utilizing digital technology are increasingly relevant for MSMEs because digitalization can help overcome limitations in market access, improve operational efficiency, and expand access to financial services. However, these benefits are not always distributed evenly because each business actor has different levels of digital competence, perceptions of technology usefulness, and infrastructure support. Kurniasari et al. (2023), in a study of 225 MSMEs in traditional Indonesian markets, found that performance expectancy influences digital adoption, and that adoption is positively related to business performance and sustainability. Furthermore, Lupiyoadi et al. (2025) showed that performance expectancy and facilitating conditions play a role in driving the intention to use artificial intelligence in MSMEs in Indonesia, while supporting conditions also influence actual use in MSME groups. These findings suggest that technology adoption needs to be understood through the interaction between user capabilities, expected benefits, and conditions that enable the technology to be used effectively. Therefore, the important issue in MSME digitalization is not merely

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how to increase technology adoption, but how to ensure that the use of technology can produce broader and more sustainable economic empowerment (Kurniasari et al., 2023; Lupiyoadi et al., 2025).

Several previous studies have provided an empirical basis for explaining the relationship between digital capabilities, technology adoption, business transformation, and economic performance. Prakasa and Jumani (2024) demonstrated that digital capability is related to business performance through digital business transformation, thus indicating the importance of the change process as a link between technological capabilities and business outcomes. Meanwhile, Liu et al. (2024) found that dynamic capabilities positively influence business model innovation and performance, and that business model innovation partially mediates the relationship between dynamic capabilities and performance. Regarding technology adoption, Kurniasari et al. (2023) demonstrated that perceived technology benefits are a factor related to MSME digital adoption. Furthermore, Sagala and Őri (2024), through a systematic review of the literature on MSME digital transformation, identified the importance of a digitalization strategy tailored to business characteristics, gradual capability enhancement, and investment in continuous education and learning. Overall, these studies demonstrate that internal capabilities, perceived benefits, and the transformation process are crucial elements in explaining the success of digitalization. However, these studies use different focuses and end results, so the relationship between these factors still needs to be studied within a more integrated digital economic empowerment framework (Kurniasari et al., 2023; Sagala & Őri, 2024).

Although the relationship between digitalization and business performance has been extensively researched, there are differences in how previous studies explain the mechanisms linking technology adoption to economic outcomes. Prakasa and Jumani (2024) emphasize digital business transformation as a mechanism linking digital capabilities to business performance, while Liu et al. (2024) highlight business model innovation and dynamic capabilities as critical elements in improving performance. Conversely, Lupiyoadi et al. (2025) focus on factors influencing artificial intelligence adoption and find that the influence of several technology acceptance factors differs between MSMEs and startups. These differences suggest that factors driving technology adoption may not necessarily have the same relationship with the ability to make changes and achieve economic benefits. Sagala and Őri (2024) also emphasize that the success of MSME digital transformation depends on the alignment of strategies with business conditions and the continuous development of capabilities. However, these findings do not directly explain how digital competence, performance expectancy, and facilitating conditions collectively relate to digital economic empowerment, either through direct influence or through transformative capacity. Thus, empirical testing is still needed to

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differentiate the influence of technology acceptance factors from transformation mechanisms that can link it to economic empowerment (Liu et al., 2024; Sagala & Őri, 2024).

This research gap lies in the need for a more integrated understanding of the role of transformative capacity as a connecting mechanism between factors of technology utilization and digital economic empowerment. Previous research tends to place business performance, business model innovation, business sustainability, or technology adoption as the primary outcomes, while this study focuses on digital economic empowerment, which includes increased revenue, market expansion, product or service diversification, access to digital capital, and economic independence. Furthermore, this study utilizes secondary data from the Digital Transformation Adoption, Social Resilience, and Community Empowerment Outcomes in Post-Pandemic Indonesia dataset, which includes 544 observations from Jakarta, Surabaya, Bandung, and Medan. This data provides a cross-city empirical context to examine the relationships between variables in a single integrated model. Based on the study by Sagala and Őri (2024) on various success factors for MSME digital transformation and the findings of Kurniasari et al. (2023) on the relationship between digital adoption and business performance and sustainability, this study raises a key question: can digital competencies, performance expectations, and enabling conditions directly drive digital economic empowerment, or do these benefits depend more on the ability of businesses and communities to make changes through transformative capacity? This question is important because the success of digitalization cannot be judged solely on the use of technology, but also on the ability to translate it into tangible economic benefits (Kurniasari et al., 2023; Sagala & Őri, 2024).

Based on these gaps, this study aims to analyze the influence of digital competence, performance expectancy, and facilitating conditions on transformative capacity and the influence of transformative capacity on digital economic empowerment. This study also examines the direct influence of these three independent variables on digital economic empowerment and the role of transformative capacity as an intervening variable in this relationship. The urgency of this research lies in the need to understand why the use of digital technology does not always produce equal economic benefits, while also identifying factors and mechanisms that can strengthen the contribution of digitalization to the economic independence of business actors. The novelty of this study lies in the integration of the three factors of technology utilization with transformative capacity and digital economic empowerment in a single empirical model based on 544 observations from four cities in Indonesia. Different from the research of Prakasa and Jumani (2024) who positioned digital business transformation as a mediator of business performance and Liu et al. (2024) who emphasized business model innovation, this study

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examines the transformation mechanism as a link to digital economic empowerment. Theoretically, this study broadens understanding of the relationship between technology acceptance factors, transformation capacity, and economic outcomes by integrating the perspectives of technology adoption and dynamic capabilities. Practically, the research results are expected to form the basis for the development of digital literacy programs, business mentoring, infrastructure provision, and MSME empowerment policies that are not only oriented towards technology adoption, but also on the ability to generate sustainable economic change and benefits (Liu et al., 2024; Prakasa & Jumani, 2024).

METHOD

Research Design and Type.

This study uses a quantitative approach with an explanatory research approach to examine the relationship between digital competence, performance expectancy, and facilitating conditions on digital economic empowerment, with transformative capacity as an intervening variable. The study was designed non-experimental because it did not involve treatment or manipulation of research variables, but rather analyzed the relationships between constructs based on available data. The quantitative approach was chosen because it allows for measurable hypothesis testing through estimation of relationship coefficients and statistical significance testing (Sugiyono, 2022; Sudaryono, 2019). This study uses secondary data sourced from the Digital Transformation Adoption, Social Resilience, and Community Empowerment Outcomes in Post-Pandemic Indonesia dataset, so the research process focuses on re-analyzing survey data, rather than collecting primary data. This approach aligns with research by Prakasa and Jumani (2024), who examined the relationship between digital capability, digital business transformation, and business performance using a quantitative approach, as well as research by Lupiyoadi et al. (2025), who applied an explanatory design and Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze factors influencing technology adoption in MSMEs and startups in Indonesia. Thus, this research design allows for testing of direct and indirect influences between constructs, in line with the research objectives (Hair & Alamer, 2022).

Population and Research Sample

The unit of analysis in this study is the respondent observations available in the research dataset, which totaled 544 observations and covered business actors or business communities in four cities in Indonesia: Jakarta, Surabaya, Bandung, and Medan. All 544 observations were used in the analysis, thus this study implemented the use of all available data in the dataset for reanalysis purposes. Therefore, the researchers did not recruit respondents, determine new samples, or conduct direct sampling. Using

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all available observations allows for model testing based on accessible data coverage, but does not necessarily guarantee that the initial sample represents all business actors in the four cities. In quantitative research, the population, unit of analysis, and sampling technique need to be explained consistently with the sources and research design used (Sugiyono, 2022; Sudaryono, 2019). Prakasa and Jumani's (2024) study, for example, used 330 small businesses using a convenience sampling technique, while Lupiyoadi et al. (2025) used 322 respondents using a purposive sampling technique. Unlike those two studies, this study did not select a new sample, utilizing all observations in the existing dataset. Therefore, the sampling technique used in this study must be distinguished from the technique used by the original researchers when collecting primary data, the procedures of which have not been fully explained in the available text.

Research Instruments and Operationalization of Variables.

The research instrument consisted of survey questions provided in the item-level survey dataset and codebook. This study did not develop or distribute a new questionnaire, but instead used 23 indicators grouped into five constructs according to the conceptual framework and operational definitions of the variables. The digital competence construct was measured using four indicators covering the ability to operate digital applications, create marketing content, maintain data security, and improve digital competency. The performance expectancy construct was measured using five indicators regarding the benefits of technology for efficiency, productivity, achievement of business goals, competitive advantage, and revenue growth. The facilitating conditions construct used four indicators related to digital infrastructure, technical support, institutional facilitation, and training. Furthermore, transformative capacity was measured using five indicators regarding business model change, structural transformation, advocacy for change, long-term vision, and integration of cultural values in digital transformation. Meanwhile, digital economic empowerment used five indicators reflecting increased revenue, market expansion, product or service diversification, access to digital capital, and economic independence. All indicators used a five-level Likert scale as stated in the research manuscript. The use of existing instruments requires checking the suitability of the indicators to the constructs being measured, as well as evaluating the validity and reliability of the analyzed data (Sugiyono, 2022; Emzir, 2021). Referring to the PLS-SEM procedure, this evaluation is conducted through examining outer loading, internal consistency, average variance extracted (AVE), and discriminant validity using the heterotrait-monotrait ratio (HTMT) (Hair & Alamer, 2022). This approach is also relevant to the research of Liu et al. (2024) and Lupiyoadi et al. (2025), which used survey instruments to examine the relationships between constructs in a study of digital technology transformation and adoption.

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Research Procedures.

The research was conducted through a series of systematic stages, starting with establishing a conceptual model based on the research objectives and previous studies, followed by identifying secondary data sources, examining the dataset and codebook, and mapping indicators into five research constructs. The dataset used was Digital Transformation Adoption, Social Resilience, and Community Empowerment Outcomes in Post-Pandemic Indonesia: Underlying Data (Item-Level Survey Dataset and Codebook), with 544 observations from Jakarta, Surabaya, Bandung, and Medan. After the indicators were mapped, a measurement model and a structural model were constructed based on the relationships formulated in the research hypothesis. The data were then analyzed using SmartPLS software through measurement model evaluation, structural model evaluation, and hypothesis testing. The next stage was to test the direct effect of each independent variable on the dependent variable, the effect of the independent variable on the intervening variable, and the indirect effect through transformative capacity. This sequence was intended to allow the analysis process to be traced back to the structure of the research model. Developing a coherent and transparent procedure is essential in reporting quantitative research so that readers can understand how the data was processed and how statistical conclusions were drawn (Sugiyono, 2022; Sudaryono, 2019). This analysis procedure also aligns with the research of Prakasa and Jumani (2024), which examined the role of digital business transformation as a mediator, and the research of Sagala and Őri (2024), which emphasized the importance of alignment between digital transformation strategy and business capacity. However, handling missing data, incomplete observations, and data exclusion rules needs to be explicitly explained when applicable, as these details were not sufficiently provided in the reviewed manuscripts.

Data Analysis Techniques.

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the help of SmartPLS software. This technique is used to estimate the structural relationships between constructs while testing the role of transformative capacity as an intervening variable. The first stage is the evaluation of the measurement model (outer model), which includes examining the outer loading value, internal reliability through Cronbach's alpha, rho_A, and composite reliability, convergent validity through AVE, and discriminant validity using HTMT. The second stage is the evaluation of the structural model (inner model), which includes examining collinearity through the variance inflation factor (VIF), coefficient of determination (R^2), effect size (f^2), and path coefficient. Next, a bootstrapping procedure is used to test the significance of the relationship between constructs based on the path coefficient, t-statistic value, and p-value. Direct

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and indirect effects are analyzed separately, with the mediation effect evaluated using specific indirect effects. The test uses a 5% significance level, i.e., a p-value less than 0.05, as the basis for declaring the tested relationship statistically significant. The use of PLS-SEM is appropriate for models involving multiple constructs and mediating relationships, but evaluation of the measurement model is still necessary before interpreting the structural relationships (Hair & Alamer, 2022). A similar approach can be found in the studies of Liu et al. (2024), Prakasa and Jumani (2024), and Lupiyoadi et al. (2025), who used variance-based SEM to examine the relationship between capabilities, transformation, technology adoption, and business outcomes. Thus, this analysis technique is used to answer all research questions by examining both direct and indirect influence mechanisms. The conceptual framework of the study is shown in Figure 1.

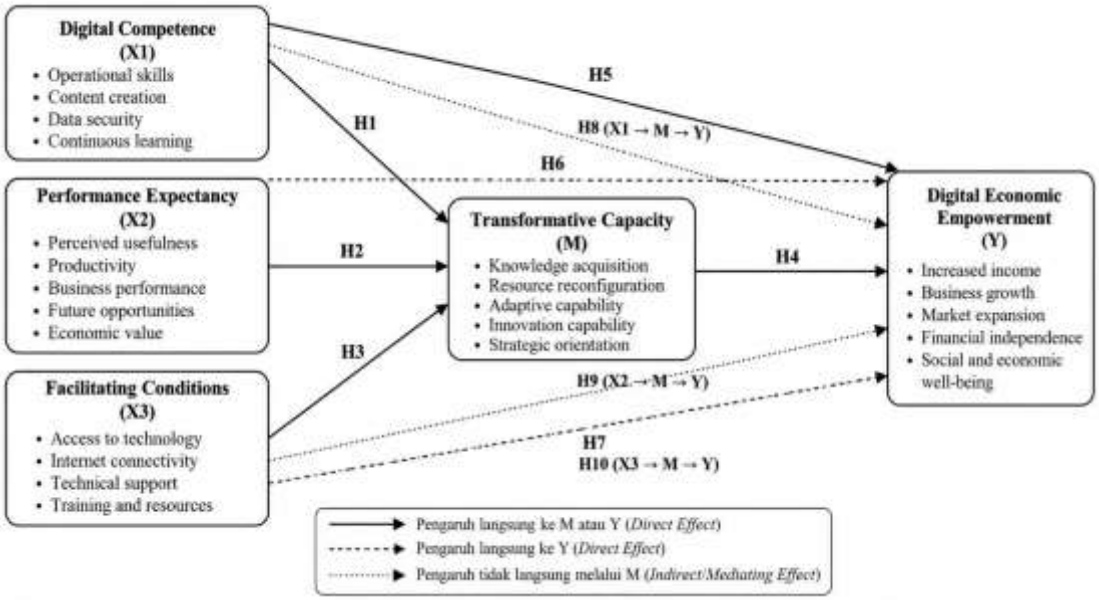


Figure 1

Ethical Considerations of Research.

This study used secondary data and did not involve the recruitment of respondents or direct interaction with participants to collect new data. However, the use of secondary data still requires consideration of access authority, dataset usage conditions, the confidentiality of respondent information, and the prohibition on re-identifying individuals if the data is anonymous. Researchers also need to ensure that the processing and presentation of results are conducted solely for scientific purposes and do not disclose information that could potentially harm the parties who serve as data sources. The principles of responsible research implementation and transparent reporting of methods must be adhered to at all stages of the research (Sugiyono, 2022; Emzir, 2021). However,

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the available manuscript does not include an ethical clearance number, a statement of exemption from ethical review, or documentation of permission to use the dataset from the data administrator. Therefore, this study cannot be considered to have obtained specific ethical approval without additional verification. Before submitting an article to a journal, authors should verify the origin of the dataset, the conditions for access and use, its anonymization status, and any applicable ethical approval information or exemption basis. Transparency regarding these aspects is crucial to maintaining research integrity and enabling editors and readers to assess the appropriateness of using the analyzed data (Sudaryono, 2019; Sugiyono, 2022).

RESEARCH RESULT

After the research model was processed using Partial Least Squares–Structural Equation Modeling (PLS-SEM) with the help of SmartPLS, the next step was to evaluate the measurement and structural models. This evaluation was conducted to ensure that the indicators and constructs met validity and reliability criteria before testing the relationships between variables and the research hypotheses.

Evaluation of Measurement Model (Outer Model)

Outer model evaluation is conducted to determine the indicators' ability to measure the research constructs. The evaluation includes outer loading values, construct reliability, convergent validity, and discriminant validity.

Table 1. Outer Loading Values

	Digital Competence (X1)	Digital Economic Empowerment (Y)	Facilitating Conditions (X3)	Performance Expectancy (X2)	Transformative Capacity (M)
DC01	**0.864**				
DC02	**0.846**				
DC03	**0.859**				
DC04	**0.858**				
ECO01		**0.802**			
ECO02		**0.841**			
ECO03		**0.840**			
ECO04		**0.791**			
ECO05		**0.834**			
FC01			**0.827**		
FC02			**0.881**		

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FC03			**0.853**		
FC04			**0.825**		
PE01				**0.859**	
PE02				**0.863**	
PE03				**0.856**	
PE04				**0.835**	
PE05				**0.808**	
TRF01					**0.847**
TRF02					**0.831**
TRF03					**0.831**
TRF04					**0.801**
TRF05					**0.831**

The outer loading values for all indicators ranged from 0.791 to 0.881. All indicators had values above 0.70, thus meeting convergent validity criteria and being retained in the research model.

Before conducting structural relationship testing, construct reliability and validity need to be checked to ensure that each construct has internal consistency and is able to explain the indicators used.

Table 2. Reliability and Construct Validity Values

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Digital Competence (X1)	**0.880**	**0.883**	**0.917**	**0.734**
Digital Economic Empowerment (Y)	**0.880**	**0.881**	**0.912**	**0.676**
Facilitating Conditions (X3)	**0.868**	**0.869**	**0.910**	**0.717**
Performance Expectancy (X2)	**0.899**	**0.899**	**0.926**	**0.713**
Transformative Capacity (M)	**0.886**	**0.887**	**0.916**	**0.686**

All constructs had Cronbach's Alpha, rho_A, and Composite Reliability values above 0.70. The AVE values for all constructs were also above 0.50. Thus, the research constructs met the criteria for reliability and convergent validity.

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Next, discriminant validity was tested using the Heterotrait-Monotrait Ratio (HTMT) approach. This test is used to determine the extent to which each construct is empirically different from the other constructs.

Table 3. Heterotrait-Monotrait Ratio (HTMT) Values

	Digital Competence (X1)	Digital Economic Empowerment (Y)	Facilitating Conditions (X3)	Performance Expectancy (X2)	Transformative Capacity (M)
Digital Competence (X1)					
Digital Economic Empowerment (Y)	0.474				
Facilitating Conditions (X3)	0.966	0.485			
Performance Expectancy (X2)	0.923	0.475	0.953		
Transformative Capacity (M)	0.473	0.607	0.466	0.430	

The HTMT results show that several inter-construct relationships have high values, especially Digital Competence with Facilitating Conditions at 0.966, Digital Competence with Performance Expectancy at 0.923, and Facilitating Conditions with Performance Expectancy at 0.953. These findings indicate a fairly strong empirical closeness between the three constructs and need to be considered in the discussion of the research results.

1.8.2 Structural Model Evaluation (Inner Model)

After evaluating the measurement model, the next step is evaluating the structural model. This evaluation aims to assess the model's ability to explain endogenous constructs and ensure there are no collinearity issues in the relationships between variables.

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Table 4. Inner VIF Values

	Digital Competence (X1)	Digital Economic Empowerment (Y)	Facilitating Conditions (X3)	Performance Expectancy (X2)	Transformative Capacity (M)
Digital Competence (X1)		4.165			4,091
Digital Economic Empowerment (Y)					
Facilitating Conditions (X3)		4,581			4,547
Performance Expectancy (X2)		4,023			4,020
Transformative Capacity (M)		**1,231**			

Inner VIF valueis in the range of 1.231–4.581. These results indicate that the model does not exhibit very high collinearity problems, although some relationships have relatively larger VIF values than others.

Table 5. R-Square Value

	R Square	R Square Adjusted
Digital Economic Empowerment (Y)	0.346	0.341
Transformative Capacity (M)	0.188	0.183

The R^2 value is used to determine how much of the variation in endogenous constructs can be explained by the exogenous constructs in the research model. The R^2 value for Transformative Capacity of 0.188 indicates that Digital Competence, Performance Expectancy, and Facilitating Conditions can explain 18.8% of the variation in Transformative Capacity. Meanwhile, the R^2 for Digital Economic Empowerment of 0.346 indicates that the model can explain 34.6% of the variation in Digital Economic

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Empowerment. In addition to R^2, the effect size is used to determine the contribution of each exogenous construct to the endogenous construct in the model.

Table 6. Effect Size Value (f^2)

	Digital Competence (X1)	Digital Economic Empowerment (Y)	Facilitating Conditions (X3)	Performance Expectancy (X2)	Transformative Capacity (M)
Digital Competence (X1)		0.001			0.018
Digital Economic Empowerment (Y)					
Facilitating Conditions (X3)		0.002			0.007
Performance Expectancy (X2)		0.009			0.001
Transformative Capacity (M)		0.223			

The results show that Transformative Capacity has an f^2 value of 0.223 on Digital Economic Empowerment, while the relationships between other constructs have relatively small f^2 values.

Hypothesis Testing

After the measurement model and structural model have completed the evaluation stage, hypothesis testing is conducted using a bootstrapping procedure. Testing is conducted on the direct effects between variables and the indirect effects through Transformative Capacity as an intervening variable.

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Table 7. Results of Direct Effect Testing

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Digital Competence (X1) -> Digital Economic Empowerment (Y)	0.042	0.042	0.071	0.591	**0.554**
Digital Competence (X1) -> Transformative Capacity (M)	0.245	0.244	0.074	3,323	**0.001**
Facilitating Conditions (X3) -> Digital Economic Empowerment (Y)	0.085	0.086	0.074	1,148	**0.251**
Facilitating Conditions (X3) -> Transformative Capacity (M)	0.165	0.167	0.080	2,078	**0.038**
Performance Expectancy (X2) -> Digital Economic Empowerment (Y)	0.154	0.155	0.066	2,354	**0.019**
Performance Expectancy (X2) -> Transformative Capacity (M)	0.044	0.044	0.070	0.629	**0.530**

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Transformative Capacity (M) -> Digital Economic Empowerment (Y)	0.424	0.425	0.037	11,471	**0.000**

Based on the results of the bootstrapping test, the relationship between X1 Digital Competence and M Transformative Capacity produces a path coefficient of 0.245, a t-statistic value of 3.323, and a p-value of 0.001. Because the p-value <0.05, X1 has a positive and significant effect on M. Thus, H1 is accepted.

Furthermore, X2 Performance Expectancy on M Transformative Capacity produces a path coefficient of 0.044, a t-statistic of 0.629, and a p-value of 0.530. A p-value > 0.05 indicates that X2 has no significant effect on M. Thus, H2 is rejected.

In the relationship between X3 Facilitating Conditions and M Transformative Capacity, the path coefficient is 0.165, the t-statistic is 2.078, and the p-value is 0.038. Because the p-value <0.05, X3 has a positive and significant effect on M. Thus, H3 is accepted.

Meanwhile, the relationship between M Transformative Capacity and Y Digital Economic Empowerment shows a path coefficient of 0.424, a t-statistic of 11.471, and a p-value of 0.000. These results indicate that M has a positive and significant effect on Y. Thus, H4 is accepted.

For the direct influence on Y, X1 Digital Competence on Y Digital Economic Empowerment produces a path coefficient of 0.042, a t-statistic of 0.591, and a p-value of 0.554. Because the p-value > 0.05, X1 does not have a significant effect on Y. Thus, H5 is rejected.

The relationship between X2 Performance Expectancy and Y Digital Economic Empowerment produces a path coefficient of 0.154, a t-statistic of 2.354, and a p-value of 0.019. These results indicate that X2 has a positive and significant effect on Y. Thus, H6 is accepted.

Finally, the relationship between X3 Facilitating Conditions and Y Digital Economic Empowerment produces a path coefficient of 0.085, a t-statistic of 1.148, and a p-value of 0.251. Since the p-value > 0.05, X3 does not have a significant effect on Y. Thus, H7 is rejected.

Indirect influence testing was conducted to determine whether Transformative Capacity acts as an intervening variable in the relationship between each exogenous variable and Digital Economic Empowerment.

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Table 8. Results of Indirect Effect Testing

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Digital Competence (X1) -> Transformative Capacity (M) -> Digital Economic Empowerment (Y)	0.104	0.104	0.033	3.125	**0.002**
Facilitating Conditions (X3) -> Transformative Capacity (M) -> Digital Economic Empowerment (Y)	0.070	0.071	0.035	2,000	**0.046**
Performance Expectancy (X2) -> Transformative Capacity (M) -> Digital Economic Empowerment (Y)	0.019	0.018	0.030	0.626	**0.531**

Based on the bootstrapping results on specific indirect effects, the relationship between X1 Digital Competence and Y Digital Economic Empowerment through M Transformative Capacity produces an indirect effect coefficient of 0.104, a t-statistic value of 3.125, and a p-value of 0.002. Because the p-value <0.05, the indirect effect of X1 on Y through M is declared significant. Thus, H8 is accepted.

Furthermore, the indirect effect of X2 Performance Expectancy on Y Digital Economic Empowerment through M Transformative Capacity produces a coefficient of 0.019, a t-statistic of 0.626, and a p-value of 0.531. Since the p-value > 0.05, the indirect effect of X2 on Y through M is not significant. Thus, H9 is rejected.

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Meanwhile, the relationship between X3 Facilitating Conditions and Y Digital Economic Empowerment through M Transformative Capacity produces an indirect effect coefficient of 0.070, a t-statistic of 2.000, and a p-value of 0.046. Since the p-value <0.05, the indirect effect of X3 on Y through M is declared significant. Thus, H10 is accepted.

Thus, the test results show that M Transformative Capacity plays a role as an intervening variable in the relationship between X1 Digital Competence and X3 Facilitating Conditions towards Y Digital Economic Empowerment. On the other hand, M does not show a significant intervening role in the relationship between X2 Performance Expectancy towards Y.

DISCUSSION

The results of the study indicate that the relationships between technology utilization, transformative capacity, and digital economic empowerment do not all occur through the same pattern. Of the seven direct influences tested, four relationships showed a significant influence, while the other three relationships were insignificant. In the indirect influence, X1 and X3 showed a significant influence on Y through M, while X2 did not show a significant indirect effect. These findings indicate that technology use does not always result in digital economic empowerment through the same mechanism.

Synthesis of Research Results

1. First, X1 Digital Competence and X3 Facilitating Conditions play a role in forming M Transformative Capacity. Both show a significant influence on M. In contrast, X2 Performance Expectancy does not show a significant influence on M.
2. Second, M Transformative Capacity is the strongest variable in explaining Y Digital Economic Empowerment. The M → Y path coefficient of 0.424 is the largest direct influence in the model. This strengthens the argument that technology use is not only seen from the ability to use or perceived benefits, but also from the ability to make changes after the technology is used.
3. Third, the relationship mechanism of each independent variable with Y is different. X1 does not have a significant direct influence on Y, but has a significant indirect influence through M. X3 shows the same pattern. Meanwhile, X2 actually has a significant direct influence on Y, but has no influence through M.

These findings suggest that transformative capacity is not simply an additional variable in the model, but plays a crucial role in explaining how certain factors translate into economic benefits. This position aligns with the research framework, which utilizes Dynamic Capability Theory to explain the change process, while TOE and UTAUT are used to explain factors related to technology utilization.

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CONCLUSION

This study shows that digital competence and facilitating conditions significantly influence transformative capacity, while performance expectancy does not. Furthermore, transformative capacity significantly influences digital economic empowerment. Directly, only performance expectancy significantly influences digital economic empowerment. Meanwhile, transformative capacity is proven to mediate the relationship between digital competence and facilitating conditions on digital economic empowerment, but not on performance expectancy. Thus, the economic benefits of digitalization in this study are stronger when technology utilization is accompanied by the ability to make changes in business or community activities.

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