Analysis of the Influence of Corporate Maturity Mismatch on the Digital Transformation of Manufacturing Companies in Indonesia

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ABSTRACT

Digital transformation has become a strategic necessity for companies to maintain competitiveness amid industry disruption. However, the adoption of digital transformation does not always run smoothly because it is influenced by the gap between the structural readiness of the company and the need for long-term investment, known as corporate maturity mismatch. This study aims to analyze the impact of the level of corporate maturity mismatch on the implementation of digital transformation in manufacturing companies listed on the Indonesia Stock Exchange (IDX) during the period 2018–2023. The method used is a quantitative approach with panel data regression analysis, and digital transformation is measured based on the intensity of digital keyword usage in company annual reports. The results indicate that corporate maturity mismatch has a positive impact on overall digital transformation, as well as on fundamental technology categories such as Artificial Intelligence, Blockchain, Cloud Computing, and Big Data. Conversely, no significant impact was found on digital transformation in extended applications technology. These findings indicate that mismatches in financial structure drive companies to respond to such pressures through investments in strategic and long-term digital technologies. This study provides important implications for policymakers and industry players in designing funding strategies and regulations to support the acceleration of national digital transformation.

ABSTRAK

Transformasi digital telah menjadi kebutuhan strategis bagi perusahaan untuk mempertahankan daya saing di tengah disrupsi industri. Namun, adopsi transformasi digital tidak selalu berjalan mulus karena dipengaruhi oleh kesenjangan antara kesiapan struktural perusahaan dan kebutuhan investasi jangka panjang, yang dikenal sebagai corporate maturity mismatch. Penelitian ini bertujuan untuk menganalisis pengaruh tingkat corporate maturity mismatch terhadap implementasi transformasi digital pada perusahaan manufaktur yang terdaftar di Bursa Efek Indonesia (BEI) selama periode 2018–2023. Metode yang digunakan adalah pendekatan kuantitatif dengan analisis regresi panel data, dan pengukuran transformasi digital dilakukan berdasarkan intensitas penggunaan kata kunci digital pada laporan tahunan perusahaan. Hasil penelitian menunjukkan bahwa corporate maturity mismatch berpengaruh positif terhadap transformasi digital secara keseluruhan, serta pada kategori teknologi fundamental seperti Artificial Intelligence, Blockchain, Cloud Computing, dan Big Data. Sebaliknya, tidak ditemukan pengaruh yang signifikan terhadap transformasi digital pada teknologi extended applications. Temuan ini mengindikasikan bahwa mismatch dalam struktur keuangan mendorong perusahaan untuk merespons tekanan tersebut melalui investasi pada teknologi digital yang strategis dan bernilai jangka panjang. Penelitian ini memberikan implikasi penting bagi pembuat kebijakan dan pelaku industri dalam merancang strategi pendanaan serta regulasi untuk mendukung percepatan transformasi digital nasional.

INTRODUCTION

The Industrial Revolution 4.0 is a milestone of major changes in the industrial world which is characterized by the widespread use of information technology to optimize business processes. This transformation enables closer integration between the physical and digital worlds through an automated, adaptive and efficient connected production system. In this context, the Industrial Revolution 4.0 contributes to the creation of new values in the industrial sector by basing itself on nine main pillars, namely big data analytics, autonomous robots, simulation, horizontal and vertical system integration, Internet of Things (IoT), cybersecurity, cloud computing, additive manufacturing, and augmented reality (Vaidya et al., 2018; Maresova et al., 2018).

In response to global demands, Indonesia's Ministry of Industry developed the *Indonesia Industry 4.0 Readiness Index* (INDI 4.0) to measure the readiness of national industrial transformation towards the digital era. INDI 4.0 is built on five main pillars, namely management and organization, human resources and culture, products and services, and factory operations, which are further described in 17 assessment areas (Indonesian Ministry of Industry, 2018a). This approach supports the national agenda of "Making Indonesia 4.0" as a strategy to revitalize the manufacturing sector, with an ambitious target of becoming one of the top ten economies in the world by 2030, increasing the contribution of net exports to 10% of GDP, doubling the productivity-to-cost ratio, and allocating 2% of GDP to R&D activities to encourage domestic innovation (Ministry of Industry Indonesia, 2018b).

As part of the acceleration of industrial transformation, the government has initiated the *National Lighthouse Industry 4.0 program* since 2019. Companies that are selected to be *lighthouses* are considered to be able to be role models in the application of industrial 4.0 technology. Until 2024, as many as 15 Indonesian manufacturing companies have been recognized in this program, including PT Kalbe Farma Tbk, PT Petrokimia Gresik, and PT Toyota Motor Manufacturing Indonesia (Indonesia Information Portal, 2024). The success of this transformation has a significant impact on the efficiency and competitiveness of the national manufacturing industry (BCG, 2015).

In practice, digital transformation in the manufacturing sector has been proven to correlate with company performance. However, the outcome of this transformation is highly dependent on the ownership structure and business scale of each company (Wei & Shen, 2025). Measuring the level of digitalization of companies can be done through the analysis of financial statements based on three main indicators, namely the DCG indicator (the number of mentions of digital technology in general), the ABCD indicator (mention of AI, blockchain, cloud computing, and big data technology), and the ADT indicator (the use of advanced digital application technology such as IoT and mobile payment) (Hu et al., 2023).

This transformation certainly requires strong financial resource support. The procurement of cutting-edge technology, the recruitment of experts, and intensive training for staff are the main needs. Continuous investment in research and development is also important for maintaining product relevance and innovation (M. Li & Wei, 2024). However, the financial challenges that companies face in meeting these transformation needs can pose the risk of funding mismatches, known as *corporate maturity mismatch* (Ma et al., 2022). This non-conformity can be actively carried out consciously to reduce debt or passive costs, due to limited access to long-term financing (Y. Wang et al., 2021).

Thus, the implementation of Industry 4.0 in Indonesia requires not only technological readiness and human resources, but also careful financial planning and long-term investment strategies. All of these elements are important foundations in realizing sustainable and competitive industrial transformation in the digital era. Therefore, this study aims to analyze the influence of corporate maturity mismatch on the digital transformation of manufacturing companies in Indonesia.

RESEARCH METHODS

This study uses quantitative research. This research is included in the explanatory research category that aims to explain the position of variables and their relationship to each other. This research is expected to explain the influence of *the level of corporate maturity mismatch* on the digital transformation implemented in the company.

Conceptual Framework and Data

A conceptual framework is used to understand the principles and concepts that underpin this research. This is necessary to be a guide of the overall research. The conceptual framework of this research is built based on the goals to be achieved. The conceptual framework to be used is as follows (Figure 1):

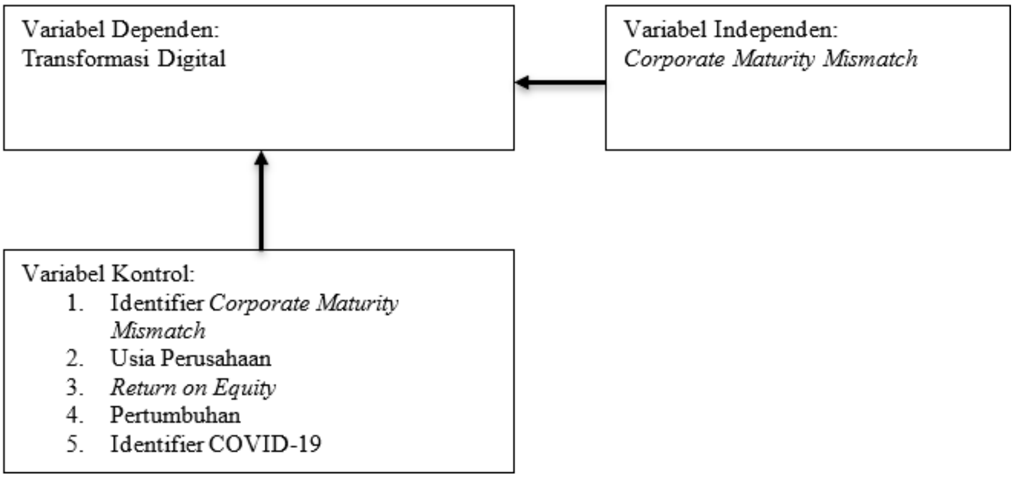

Figure 1. Conceptual Shells of Research

Source: Processed Author, 2025

The data that will be used in the research are annual data and data published in a certain period during 2018-2023. This period was chosen because *Making* Indonesia 4.0 began to be emphasized to companies in the manufacturing industry since 2018. The data sources used are annual reports and financial data of manufacturing companies in Indonesia, where annual reports and financial data will be used to analyze the following data:

1. Keyword indicators to measure the level of a company's digital transformation will be taken from the company's annual report. The annual report is obtained by combining documents downloaded from the company's website and the IDX.
2. The financial information used to calculate *corporate mismatch maturity* and other control variables is taken from the company's financial data obtained from the Capital IQ S&P Global website.

Research Variables

This study examines three main types of variables: dependent, independent, and control variables. The dependent variable in this study is the company's digital transformation, which is measured through the extraction of keywords from the company's annual report using the R program. Each category reflects a digital transformation level that ranges from 0 to 5. The measurement of this variable is divided into three indicators, namely the DCG indicator (total level of digital transformation), the ABCD sub-indicator (fundamental categories: AI, Blockchain, Cloud, and Big Data), and the ADT sub-indicator (the advanced application category such as e-commerce and digital marketing).

The independent variable in this study is Corporate Maturity Mismatch (CMM), which shows a mismatch between long-term investments and long-term funding sources. CMM is calculated by subtracting the total investment by the amount of long-term funding and operating cash flow, then divided by the previous year's total assets. A CMM value of > 0 indicates a mismatch that has the potential to encourage companies to use short-term funding for digitalization financing, while a value of ≤ 0 indicates no mismatch.

This study also controlled for a number of other variables. First, the Dummy CMM is used to identify the existence of mismatches in binary terms (0 = not occurring, 1 = occurring). Second, the age of the company (Age) is calculated through the natural logarithm of the age of the company, because age can affect the tendency of companies to adopt digitalization. Third, Return on Equity (ROE) is used as an indicator of financial performance that may have an impact on digital transformation decisions, as companies with high ROE tend to hold back transformation costs. Fourth, company growth is measured from changes in operating profits, where high-growth companies tend to be more cautious about digital transformation costs. Finally, the COVID-19 variable is used to identify the global crisis period (2020–2021), which encourages the acceleration of digitalization in response to the impact of the pandemic. Variable Direction Prediction in the Regression Model is shown in Table 1.

Table 1. Prediction of Variable Direction in Regression Models

Variable Dependency	Independent Variables	Direction Expectations
DCG	CMM	+ or -
	CMM *Dummy*	+ or -
	Age	+ or -
	ROE	-
	Growth	-
	COVID *Dummy*	+
ABCD	CMM	+ or -
	CMM *Dummy*	+ or -
	Age	+ or -
	ROE	-
	Growth	-
	COVID *Dummy*	+
ADT	CMM	+ or -
	CMM *Dummy*	+ or -
	Age	+ or -
	ROE	-
	Growth	-
	COVID *Dummy*	+

Source: Processed Author, 2025

Research Model

Referring to the reference research model, the approach used in the panel data regression model in this study is *Fixed Effect Model* (FEM) (Hu et al., 2023). FEM assumes coefficients *slope* in each variable is constant but the intercept value in each data *cross section* different (Gujarati et al., 2003), which in this study will measure the individual (company) effect model and the time effect model.

The model used in this study is:

1. The regression model for digital transformation across all technology categories is as follows:
   $Yit(DCG) = \beta 1 + \beta 2CMM_{it-1} + \beta 2CMMDummyit + \beta 3AGEit + \beta 4ROE_{it} + \beta 5Growth_{it} + \beta 6COVIDit + \Sigma Year + ui$ (1a)
2. The regression model for digital transformation in the fundamental technology category is as follows:
   $Yit(ABCD) = \beta 1 + \beta 2CMM_{it-1} + \beta 2CMMDummyit + \beta 3AGEit + \beta 4ROE_{it} + \beta 5Growth_{it} + \beta 6COVIDit + \Sigma Year + ui$ (1b)
3. The regression model for digital transformation in the extended applications technology category is as follows:
   $Yit(ADT) = \beta 1 + \beta 2CMM_{it-1} + \beta 2CMMDummyit + \beta 3AGEit + \beta 4ROE_{it} + \beta 5Growth_{it} + \beta 6COVIDit + \Sigma Year + ui$ (1c)

Where:

Yit	: Variable dependency
i	:Company
t	: Year of observation
DCG	: Corporate digital transformation (a technology-wide indicator)
ABCD	: Corporate digital transformation (technology indicators *artificial intelligence, blockchain, cloud computing,* and *big data*)
ADT	: Corporate digital transformation (indicator *extended application* digital technologies, such as *Fintech, Internet of Things, mobile payment and smart home,* etc.)
B1	: Konstanta
CMMit-1	: Level *corporate maturity mismatch* Company in the previous year
CMMdummyit	: Corporate maturity mismatch identifier, where 1 means the company has a corporate maturity mismatch and 0 means the company does not experience a corporate maturity mismatch
Ageit	: Natural logarithm of the age of the company
ROEit	: Net profit divided by total equity
Growthit	: Percentage of operating revenue this year compared to last year
COVIDit	: Identifying COVID-19, where 1 (one) means the company is in the COVID period and 0 (zero) means the company is not in the period
Off	: *Random error*

Research Hypothesis

The hypothesis of this study is to test the influence of *the level of corporate maturity mismatch* on the level of corporate digital transformation. This will be answered through regression of the regression results in the following equation:

H1a: *Corporate maturity mismatch* affects the company's digital transformation in all technology categories (DCG)

Hypothesis 1a aims to test the effect of *the level of corporate maturity mismatch* on the level of digital transformation of the company in the entire technology category, which will be answered at the *coefficient β2* in the following regression model:

$Yit(DCG) = \beta 1 + \beta 2CMM_{it-1} + \beta 2CMMDummyit + \beta 3AGEit + \beta 4ROE_{it} + \beta 5Growth_{it} + \beta 6COVIDit + \Sigma Year + ui$ (1a)

H1b: *Corporate maturity mismatch* affects the company's digital transformation in the fundamental technology category (ABCD)

Hypothesis 1b aims to test the influence of *the level of corporate maturity mismatch* on the level of digital transformation of the company in the fundamental technology category, which will be answered at the *coefficient β2* in the following model regression:

$Yit(ABCD) = \beta1 + \beta2CMM_{it-1} + \beta2CMMDummyit + \beta3AGEit + \beta4ROE_{it} + \beta5Growth_{it} + \beta6COVIDit + \Sigma Year + ui$ (1b)

H1c : *Corporate maturity mismatch* affects the company's digital transformation in the extended *applications* (ADT) category

Hypothesis 1c aims to test the effect of *the level of corporate maturity mismatch* on the level of digital transformation of the company in the category of extended applications technology, which will be answered at the *coefficient β2* in the following model regression:

$Yit(ADT) = \beta1 + \beta2CMM_{it-1} + \beta2CMMDummyit + \beta3AGEit + \beta4ROE_{it} + \beta5Growth_{it} + \beta6COVIDit + \Sigma Year + ui$ (1c)

Analysis Method

The initial stage begins with a descriptive statistical analysis that aims to provide an overview of the characteristics of the data. This analysis includes the calculation of the minimum, maximum, median, average, standard deviation, and skewness of each variable. Furthermore, a classical assumption test was carried out to ensure the validity of the regression model used. This classical assumption test consists of four types of tests, namely normality test, multicollinearity test, heteroscedasticity test, and autocorrelation test. The normality test aims to ensure that the residual in the model is distributed normally, with the skewness indicator being in the range of -2 to 2; If it is not met, then treatment is carried out with the winsorization method. The multicollinearity test was used to identify the correlational relationship between independent variables, which was characterized by a Variance Inflation Factor (VIF) value of more than 5; The handling is carried out through the centering technique. The heteroscedasticity test used *the Modified Wald Test for Groupwise Heteroskedasticity* for the panel data, while the autocorrelation test was performed with *the Wooldridge Test for Autocorrelation*. If there is a violation of one of the classical assumptions, then *a robust standard errors* approach will be applied to maintain the validity of parameter estimation.

In the next stage, the Hausman Test is carried out to determine the most suitable panel regression model between *random effects* and *fixed effects*. This test serves to test whether individual error components correlate with independent variables, based on decision-making based on probability values compared to significance levels (α). If the probability value is less than α, then *the fixed effect model* is more suitable, and vice versa. After the appropriate regression model is determined, the analysis is continued with regression results testing which includes three types of tests, namely: F test to determine the simultaneous significance of independent variables to dependent variables, t-test to determine the partial influence of each independent variable, and Determination Coefficient Test (Adjusted R^2) to assess the proportion of variations in dependent variables that can be explained by independent variables. The entire analysis was carried out using the Stata software, which provides the statistical outputs needed to test the hypothesis empirically and comprehensively.

A strong conceptual framework should be explicitly connected to the underlying theoretical perspectives that explain why a Corporate Maturity Mismatch (CMM) could influence digital transformation outcomes. For instance, the pecking order theory and resource-based view (RBV) can help clarify the mechanism: firms with a mismatch in long-term funding may be forced to rely on short-term financing, which can either accelerate digital adoption as a survival strategy or delay transformation due to liquidity constraints. Thus, it is critical to explain whether CMM pushes firms into digital transformation because of efficiency pressures, or hinders it due to financial rigidity. This theoretical anchoring will provide readers with a clearer rationale for the hypothesized relationships in the model.

Furthermore, the measurement of digital transformation via keyword intensity in annual reports should be strengthened with a clear justification. While text-based indicators capture disclosure and strategic signaling, they may not fully reflect actual transformation. To increase validity, triangulation could be performed using IT expenditure data, the number of digital projects, or survey-based digitalization indices as complementary measures. Clarifying the inclusion-exclusion criteria of firms, reporting the number of companies observed, and providing their size distribution, sub-sector breakdown, and ownership profiles will also help contextualize the findings. External factors, such as sectoral regulation, global technology shocks, or policy incentives, should be considered when interpreting low adjusted R^2 values, as these may capture omitted variables beyond firm-level mismatches. Robustness checks—such as dynamic panel models (e.g., GMM)—are recommended to address endogeneity and persistence in digital adoption, while theoretical explanations should be offered for why certain controls (e.g., high ROE or rapid growth) exert a negative rather than positive effect on digital transformation.

RESULTS AND DISCUSSION

Result

Classic Assumption Test

Normality Test

In the Descriptive Statistics table Before *Winsorization*, it can be seen that there are several variables that have *a skewness* of less than -2 or more than 2. The variables in question include ABCD, CMM, ROE, and *Growth*. This indicates that the data is not distributed normally. The data requires *winsorization treatment.* After the data is treated *winsorization*, the data is assumed to have been distributed normally as shown in the table below.

Table 2. Descriptive Statistics After Winsorization

Variable	*Min*	*Max*	*Median*	*Mean*	*Standard Deviation*	*Skewness*
DCG	0.000	0.699	0.000	0.143	0.192	0.865
ABCD	0.000	0.301	0.000	0.046	0.109	1.921
ADT	0.000	0.301	0.000	0.107	0.144	0.606
CMM	-0.363	0.174	-0.059	-0.073	0.137	-0.386
CMM *Dummy*	0.000	1.000	0.000	0.294	0.456	0.903
Age	1.609	5.318	3.807	3.786	0.399	-0.209
ROE	-0.234	0.363	0.066	0.067	0.133	-0.101
Growth	-0.369	0.475	0.044	0.046	0.207	2.507
COVID	0.000	1.000	0.000	0.333	0.471	0.707

Source: Stata with Author's Processing, 2025

Multicollinearity Test

In Stata, the existence of multicollinearity is indicated if the VIF value is more than 5. The test results on all models 1a, 1b, and 1c showed the absence of multicollinearity because the VIF value was less than 5. Therefore, it can be concluded that the classical assumption test of multicollinearity is fulfilled and does not require *further treatment*. The following are the results of the multicollinearity test:

Table 3. Multicollinearity Test Results

Variable	BRIGHT
CMM	2.220
CMM *Dummy*	2.030
ROE	1.010
Age	1.010
Growth	1.010
COVID *Dummy*	2.030
Mean VIF	1.440

Source: Stata with Author's Processing, 2025

Hetero Test

In Stata, the research model is indicated to have a heteroscedastic problem if the probability of R-square is less than alpha. The test results show that there is a heteroscedastic issue for all research models, where the probability of R-square is less than alpha. All research models 1a, 1b, and 1c are heteroscedastic so that they require *treatment* by running regression *error robust* on Stata.

Table 4. Heteroscedastic Test Results of Research Model 1a

F(6, 569)	7.17	**Prob > F**	0.000
Within R-squared	0.073	**Prob > chi2**	0.000

Source: Stata with Author's Processing, 2025

Table 5. Heteroscedastic Test Results of Research Model 1b

F(6, 569)	2.31	**Prob > F**	0.032
Within R-squared	0.024	**Prob > chi2**	0.000

Source: Stata with Author's Processing, 2025

Table 6. Heteroscedastic Test Results of Research Model 1c

F(6, 569)	6.49	**Prob > F**	0.000
Within R-squared	0.064	**Prob > chi2**	0.000

Source: Stata with Author's Processing, 2025

Otolaryngation Test

In Stata, the research model is indicated to have an autolocalization problem if the probability of F is less than alpha. The test results show that there is an autocratic issue for the 1b research model. So the 1b research model requires *treatment* by running regression *robust standard error*.

Table 7. Results of the Otolaryngation Test of Research Model 1a

F(1, 114)	16.315	**Prob > F**	0.000

Source: Stata with Author's Processing, 2025

Table 8. Results of the Otolaryngation Test of Research Model 1b

F(1, 114)	0.311	**Prob > F**	0.578

Source: Stata with Author's Processing, 2025

Table 9. Results of the Otolaryngation Test of the 1c Research Model

F(1, 114)	8.664	**Prob > F**	0.004

Source: Stata with Author's Processing, 2025

Hausman Test

In Stata, a more appropriate research model was used to test panel data regression using the Hausman test. The *fixed effect* research model is more appropriate if the probability is less than alpha while *the random effect* research model is more appropriate if the probability is more than alpha. The test results show that all studies are more appropriate using *the fixed effect* model.

Table 10. Hausman Test Results of Research Model 1a

Chi2	19.71	**Prob > chi2**	0.003

Source: Stata with Author's Processing, 2025

Table 11. Hausman Test Results of Research Model 1b

Chi2	20.57	**Prob > chi2**	0.002

Source: Stata with Author's Processing, 2025

Table 12. Hausman Test Results of Research Model 1c

Chi2	26.98	**Prob > chi2**	0.000

Source: Stata with Author's Processing, 2025

Analysis of Regression Results

Regression Results of Research Model 1a

Based on the table below, it can be concluded that model 1a has an F-stat value of 4.790 with an F-stat probability of 0.000 which means that the research model used is significant. This illustrates that the independent variables together have a significant effect on the dependent variables.

Table 13. Data Regression Results Panel *Fixed Effect Cluster Robust* Research Model 1a

Model Hypothesis 1a

Yit(DCG) = β1 + β2L.CMM$_{it-1}$ *+ β2CMMDummyit + β3AGEit + β4ROE*$_{it}$ *+ β5Growth*$_{it}$ *+ β6COVIDDummyit + ΣYear + ui (1a)*

H1a: The level *of corporate maturity mismatch* affects the company's digital transformation in the entire technology category (DCG)

Variabel	Expectations	Coeficin	Probability	Significance
C		-1.595	0.000	***
CMM	+ or -	0.088	0.095	*
CMM Dummy	+ or -	-0.011	0.442	
Age	+ or -	1.066	0.000	***
ROE	-	-0.078	0.064	*
Growth	-	-0.049	0.046	**
COVID Dummy	+	0.005	0.512	

Model Hypothesis 1a			
Yit(DCG) = β1 + β2L.CMM$_{it-1}$ + β2CMMDummyit + β3AGEit + β4ROE$_{it}$ + β5Growth$_{it}$ + β6COVIDDummyit + ΣYear + ui (1a)			
H1a: The level *of corporate maturity mismatch* affects the company's digital transformation in the entire technology category (DCG)			
Within R-Square	0.070	F-stat	4.790
		F-Stat Probabilities	0.000
Remarks:*** significant at α = 1%** significant at α=5%* significant at α=10%			

Source: Stata with Author's Processing, 2025

In research model 1a, an Within R-square value of 0.070 indicates that only 7% of the variation in the rate of corporate digital transformation across the entire technology category (DCG) can be explained by the independent variables and control variables used in the model. Thus, about 93% of the remaining are affected by other factors that are not included in this model. One of the main independent variables, namely *Corporate Maturity Mismatch* (CMM), shows a coefficient of 0.088 with a probability value of 0.095. These results show that CMM has a positive and significant effect on digital transformation. This finding is in line with a literature review that states that the mismatch of corporate maturity with external environmental dynamics, as a form of disruption, actually encourages companies to carry out digital transformation to create added value. This transformation initiative is expected to improve operational efficiency, company performance, and encourage broader industry growth (Vial, 2019).

Meanwhile, some control variables showed mixed results. The *Dummy CMM variable* has a coefficient of -0.011 with a probability of 0.442, indicating a negative but not significant influence on digital transformation. This suggests that the existence of binary mismatches (their presence or not) is not enough to explain the rate of digital adoption, and that the intensity of mismatches is more relevant as a key driver. In contrast, the age of the company (*Age*) showed a positive and significant influence, with a coefficient of 1.066 and a probability of 0.000. These results are consistent with the hypothesis that more mature companies tend to have greater financial capacity and resources to support digital transformation (Q. Wang et al., 2024).

Interestingly, the profitability variable measured through *Return on Equity* (ROE) shows a negative coefficient of -0.078 with a probability value of 0.064, which means that ROE has a negative and significant effect on digital transformation at a significance level of 10%. These findings support the argument that companies with high rates of return on capital tend to be cautious in allocating funds for digital transformation due to the high upfront costs required in the technology implementation phase (Hu et al., 2023). A similar pattern was also found in the *Growth* variable, which had a coefficient of -0.049 with a probability of 0.046. These results show that companies that experience high growth tend to hold back digital transformation initiatives in order to maintain short-term growth sustainability (Zhu et al., 2024).

Finally, the *COVID Dummy variable* shows a positive coefficient of 0.005 with a probability of 0.512, which means that there is no significant influence between the COVID-19 pandemic conditions and the company's overall digital transformation. These results show that, in aggregate, the pandemic conditions did not directly drive the acceleration of digital adoption across technology categories, in contrast to the common assumption that the pandemic was the main catalyst for digital transformation.

Regression Results of Research Model 1b

Based on the table below, it can be concluded that model 1b has an F-stat value of 2.110 with an F-stat probability of 0.058 which indicates that the research model used is significant. This illustrates that the independent variables together have a significant effect on the dependent variables.

Table 14. Regression Results of Robust Panel Data *Solid* Research Model 1b

Model Hypothesis 1b

Yit(ABCD) = β1 + β2L.CMM$_{it-1}$ + β2CMMDummyit + β3AGEit + β4ROE$_{it}$ + β5Growth$_{it}$ + β6COVIDDummyit + ΣYear + ui (1b)

H1b: The level *of corporate maturity mismatch* affects the company's digital transformation in the fundamental technology category (ABCD)

Variabel	Expectations	Coeficin	Probability	Significance
C		-0.323	0.262	
CMM	+ or -	0.085	0.018	**
CMM Dummy	+ or -	-0.023	0.031	**
Age	+ or -	0.237	0.177	
ROE	-	-0.056	0.106	
Growth	-	-0.013	0.466	
COVID Dummy	+	-0.003	0.541	
Within R-Square	0.024		F-stat	2.110
			F-Stat Probabilities	0.058

Remarks:*** significant at α = 1%** significant at α=5%* significant at α=10%

Source: Stata with Author's Processing, 2025

The greater the value of Within R-square indicates that the greater the ability of the independent variable to explain the dependent variable. In the 1a research model, Within R-square has a value of 0.024 which means that only 2.4% of the variation of the digital transformation sample can be represented by independent variables and control variables. While the rest of the variation is explained by other factors that are not found in the research model

The influence of independent variables and control variables based on regression results is described as follows:

Variabel Independen – *Corporate Maturity Mismatch* (CMM), The influence of independent variables (CMM) has a coefficient of 0.085 with a probability value of 0.018. This shows that the CMM variable has a positive and significant effect on the level of digital transformation of companies in the fundamental technology category (ABCD). This result is in accordance with the literature review research where the disruption faced by the company is actually responded to by implementing digital transformation (Vial, 2019). The significance of the influence of CMM variables on digital transformation in this fundamental technology category is higher than its influence on digital transformation in the overall technology category. This shows that if the technology category that is *an extended application* is excluded from the digital transformation indicator, the significance of the CMM variable becomes stronger.

Variable Control, *Corporate Maturity Mismatch Dummy* (CMM *Dummy*), The Dummy CMM has a coefficient of -0.023 with a probability value of 0.031. This shows that the *Dummy CMM variable* has a negative and significant effect on the level of digital transformation of companies in the fundamental technology category (ABCD). These results are in accordance with the research hypothesis, where companies that experience *corporate maturity mismatch* tend to implement digital transformation (Hu et al., 2023), especially in the fundamental technology category. Company Age The age of the company has a coefficient of 0.237 with a probability value of 0.177. This shows that the *Age variable* has a positive but not significant effect on the level of digital transformation of companies in fundamental technology (ABCD). The results of this study are not in accordance with the research hypothesis that was constructed, where the age of the company does not have a significant influence on the implementation of digital transformation in the category of fundamental technology (ABCD).

Return on Equity (ROE), The ROE has a coefficient of -0.056 with a probability value of 0.106. This shows that the ROE variable has a negative but not significant effect on the level of digital transformation of companies in the fundamental technology category (ABCD). The results of this study are not in accordance with the research hypothesis that was built, where companies that have a higher ROE do not have a significant influence on the implementation of digital transformation in the fundamental technology category (ABCD).

Growth, The company's growth has a coefficient of -0.013 with a probability value of 0.466. This shows tha the *Growth* variable has a negative but not significant effect on the level of digital transformation of companies in the fundamental technology category (ABCD). The results of this study are not in accordance with the research hypothesis built in which companies that have higher growth do not have a significant influence on the implementation of digital transformation in the category of fundamental technology (ABCD).

COVID-19 (COVID *Dummy*), The COVID-19 variable has a coefficient of -0.003 with a probability value of 0.541. This shows that the COVID *Dummy* variable has a positive but insignificant effect on the level of digital transformation of companies in the fundamental technology category (ABCD). The results of this study are not in accordance with the research hypothesis that was built, where the implementation of digital transformation in the fundamental technology category is not significantly influenced by the conditions when the company faces the COVID-19 pandemic or not.

Regression Results of Research Model 1c

The regression model 1c showed statistically significant results, with a statistical F-value of 4.790 and a statistical F-probability of 0.000. This indicates that the independent variables used in the model, simultaneously, have a significant effect on the dependent variable, namely the level of digital transformation of the company in the extended applications (ADT) technology category. However, the Within R-square value of only 0.064 indicates that this model is only able to explain about 6.4% of the variation in the company's digital transformation, while the rest is explained by other factors outside the research model.

In this model, the main independent variable, namely *Corporate Maturity Mismatch* (CMM), has a coefficient of 0.012 with a probability value of 0.796. Although the direction of influence is positive, this influence is not significant, which means that the mismatch of corporate maturity does not play a major role in driving digital transformation in the extended applications technology category. This may be due to the characteristics of this type of technology that does not require large investments, so that even companies with mismatches can still adopt it without significant obstacles. These results do not support the initial hypothesis that mismatch will drive accelerated digital adoption.

Meanwhile, the control variable gives varied results. *The Dummy CMM* has a negative coefficient of -0.005 with a probability value of 0.627, indicating the absence of significant influence, and contradicts the initial hypothesis. On the other hand, the company age variable (*Age*) had a positive and significant effect with a coefficient of 0.877 and a probability of 0.000. This supports the assumption that more mature companies have a greater capacity to adapt to digital transformation, both in terms of financing and organizational structure readiness (Q. Wang et al., 2024).

The *Return on Equity* (ROE) variable has a coefficient of -0.019 and a probability of 0.566, indicating a negative influence that is not significant. This means that the company's profitability level does not directly affect the decision to adopt extended applications technology. These results do not match the initial hypothesis, which predicts that more profitable companies will be more aggressive in undertaking digital transformation. In contrast, the *Growth* variable showed a negative and significant influence, with a coefficient of -0.037 and a probability of 0.024. This reinforces the argument that companies with high growth rates tend to be more cautious in undertaking digital transformation due to the priority of short-term growth sustainability (Zhu et al., 2024).

Interestingly, the *COVID Dummy variable* showed a positive and significant influence on digital transformation, with a coefficient of 0.011 and a probability of 0.097. These findings support the hypothesis that the COVID-19 pandemic is a trigger for the acceleration of digital transformation, especially in the development of extended applications technology. Many companies are responding to the crisis by expanding the use of digital platforms such as e-commerce and other online services, as an adaptive strategy to ensure business continuity during periods of physical activity restrictions (Liu et al., 2025).

Table 15. Data Regression Results Panel Fixed Effect Cluster Robust Research Model 1c

Model Hypothesis 1c

$Yit(ADT) = \beta 1 + \beta 2L.CMM_{it-1} + \beta 2CMMDummyit + \beta 3AGEit + \beta 4ROE_{it} + \beta 5Growth_{it} + \beta 6COVIDDummyit + \Sigma Year + ui$ *(1c)*

H1c: The level *of corporate maturity mismatch* affects the company's digital transformation in the technology category of *extended applications* (ADT)

Variabel	Expectations	Coeficin	Probability	Significance
C		-1.337	0.00	***
CMM	+ or -	0.012	0.796	
CMM Dummy	+ or -	-0.005	0.627	
Age	+ or -	0.877	0.000	***
ROE	-	-0.019	0.566	
Growth	-	-0.037	0.024	**
COVID Dummy	+	0.011	0.097	*
Within R-Square	0.064		F-stat	4.790
			F-Stat Probabilities	0.000

Remarks:*** significant at α = 1%** significant at α=5%* significant at α=10%

Source: Stata with Author's Processing, 2025

Discussion

The regression analysis in Models 1a, 1b, and 1c provides an in-depth understanding of the influence of Corporate Maturity Mismatch (CMM) on the level of digital transformation of companies, both overall and in the categories of fundamental technology (ABCD) and extended application technology. In general, all three models showed statistical significance with F-statistical values of 4.790 (p = 0.000) in Model 1a, 2.110 (p = 0.058) in Model 1b, and 4.810 (p = 0.000) in Model 1c, respectively. However, the relatively low Within R-square values—0.070 for Models 1a and 1c, and 0.024 for Model 1b—indicate that the variables in the model are only able to explain a small fraction of the variation in digital transformation, while other external factors play a dominant role.

The main focus of the analysis is the influence of CMM variables that consistently show positive and significant effects on digital transformation. The CMM coefficient ranged from 0.085 to 0.088 with a probability value below or close to the significance threshold ($p < 0.1$), which confirms that the intensity of corporate maturity mismatches encourages companies to adopt digital technologies, both in the context of digital transformation in general and in fundamental technologies and extended applications. These findings are in line with related literature that emphasizes that organizational mismatch with external dynamics spurs strategic adaptation through digitalization (Vial, 2019; Song et al., 2024).

However, the Dummy CMM variable that represents the existence of a mismatch binarily shows different results. In Model 1b, this variable had a negative and significant effect (coefficient = -0.023; $p = 0.031$), indicating that the existence of mismatches without sufficient intensity was actually related to a lower rate of digital transformation, especially in fundamental technologies. Meanwhile, in Models 1a and 1c, the Dummy CMM showed a negative but not significant coefficient, indicating that the mere existence of mismatch was not enough to drive digital transformation without paying attention to the level of mismatch intensity.

In addition to the main variables, some control variables exhibit varying roles. Age of firms consistently exerts a positive and significant influence on Models 1a and 1c, with a coefficient of 1.066 and a significance level of $p = 0.000$, which supports the hypothesis that companies with a more mature age have greater resources and capacity to adopt digital technologies, particularly in extended application technologies (Q. Wang et al., 2024). In contrast, in Model 1b, the influence of age was not significant ($p = 0.177$), indicating that in the context of fundamental technology, the age of the company was not the dominant factor.

The variables of profitability (ROE) and growth (Growth) show a pattern of negative and significant influences on digital transformation in Models 1a and 1c. These results indicate that companies with high levels of profitability and growth tend to be cautious about allocating resources for digital transformation, likely due to high risks and initial investment costs (Hu et al., 2023; Zhu et al., 2024). However, in Model 1b, these two variables did not show a significant influence.

The COVID Dummy variable consistently exhibits positive but insignificant coefficients across the model, indicating that while the COVID-19 pandemic has driven widespread digitalization, its impact is not universal across all categories of digital transformation. This shows that the company's internal readiness, such as organizational structure and digital strategy, remains a key determining factor in the successful adoption of digital technology.

Overall, the results of the analysis confirm that Corporate Maturity Mismatch is an important determinant in driving corporate digital transformation, especially in fundamental technology and extended applications. The dynamics of the influence of different control variables between models indicate that the digital transformation process is strongly influenced by the specific context of the type of technology and the level of intensity of the internal challenges faced by the company. Therefore, digital transformation strategies need to consider the level of internal mismatch as well as the readiness of resources so that digital adaptation can run optimally in the face of competitive pressures and dynamic external changes.

The academic contribution of this study lies in its ability to empirically link the concept of corporate maturity mismatch (CMM) with the process of digital technology adoption, thereby enriching the theoretical dialogue on financial structure and strategic transformation. While prior research has emphasized financial constraints or organizational readiness as determinants of digital transformation, this study demonstrates that mismatches in long-term investment and funding can serve as both a constraint and a catalyst, depending on their intensity. By showing that CMM exerts a positive and significant influence on digital transformation across different technology categories, the findings extend the theoretical scope of CMM beyond traditional corporate finance outcomes and embed it within the broader literature on technological change and organizational adaptation. This not only advances the understanding of how financial structures shape innovation pathways but also highlights a nuanced mechanism where mismatch intensity, rather than its binary existence, drives strategic digitalization.

At the same time, several limitations warrant acknowledgment and provide avenues for future research. First, the relatively low explanatory power (R^2) suggests the presence of omitted variables, such as industry-specific digital readiness, leadership orientation, or policy interventions, which could be examined through moderation analysis. Second, the reliance on keyword-intensity measures introduces linguistic bias, and future studies could incorporate non-linguistic indicators such as IT expenditures, patent filings, or project-level data to capture digitalization more robustly. Third, the focus on Indonesian manufacturing firms limits generalizability; comparative studies across industries or regions would help validate whether the CMM-digitalization nexus is context-dependent. Finally, longitudinal extensions using dynamic panel models or structural equation modeling could clarify causal pathways and uncover feedback loops between financial mismatches and technological adoption, thereby offering richer insights into the evolving dynamics of digital transformation.

CONCLUSION

This study aims to examine the influence of *corporate maturity mismatch* on the level of digital transformation implemented by companies, focusing on manufacturing companies listed on the Indonesia Stock Exchange (IDX) during the 2018–2023 period. The selection of the manufacturing industry is based on the consideration of the large population and its relevance to the national policy of Making *Indonesia 4.0*, which is strategically driving digital transformation in the sector.

Based on the results of empirical model testing, this study produced several key findings. First, *corporate maturity mismatch* has proven to have a positive effect on overall digital transformation, both in the fundamental technology category and *extended applications*. This shows that the mismatch between the company's financial structure and its investment needs is an important trigger for companies to respond to these challenges through digital transformation initiatives as a form of value *creation*. This transformation is believed to be able to increase operational efficiency, improve company performance, and strengthen industry competitiveness.

Second, further test results show that the positive influence of *corporate maturity mismatch* is stronger in the fundamental technology category which includes *Artificial Intelligence*, *Blockchain*, *Cloud Computing*, and *Big Data*. These technologies require greater investment and resources, so companies with high mismatch rates are encouraged to transform more deeply to offset financial pressures and maintain long-term business sustainability. Third, although it still shows a positive direction, the influence of *corporate maturity mismatch* on digital transformation in the *extended applications* category is not statistically significant. This indicates that *extended technologies* that are generally lighter in terms of funding and resources can be implemented more flexibly without having to be triggered by internal mismatch conditions of the company.

Overall, it can be concluded that the higher the level of *corporate maturity mismatch* experienced by manufacturing companies in Indonesia, the greater the incentive for companies to carry out digital transformation, especially in technology categories that require long-term investment and are fundamental to business sustainability.

Limitations of Research and Advice

This research has several limitations that need to be considered as a basis for the development of further studies. First, the measurement of the level of digital transformation in this study is based on the use of keywords that have been defined in previous studies. This approach has the potential to ignore any variations in terminology or semantic innovations that may arise in the context of corporate reporting, so the scope of digital transformation measurement can become less comprehensive. Therefore, future research is recommended to refine the keyword list with a broader lexical or semantic approach as well as take into account the latest linguistic dynamics in corporate reporting.

Second, the measurement *of corporate maturity mismatch* refers to a formula based on long-term financial indicators, such as cash flow for capital expenditures, long-term loans, equity additions, and fixed assets. While this approach is relevant for identifying structural financial pressures, further research is expected to complement by considering short-term financial components in order to provide a more holistic picture of mismatch.

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